The Skewness of Commodity Futures Returns

Adrian Fernandez-Perez*, Bart Frijns**, Ana-Maria Fuertes*** and Joëlle Miffre****

Abstract

This article studies the relationship between total skewness and subsequent returns in commodity futures markets. Skewness risk is found to command a negative risk premium and to price the cross-section of commodity futures returns better than exposures to the backwardation and contango risk factors previously identified. Systematically buying commodities with low total skewness and shorting commodities with high total skewness generates a significant excess return of 8% a year, which is not merely a compensation for the risks associated with backwardation and contango. The findings are robust to various specifications of the asset pricing model, transaction costs, liquidity considerations, sample periods, and portfolio formation variants.

Keywords: Skewness; Commodity futures; Backwardation; Contango; Lottery-like payoffs

JEL classification: G13, G14

First version: May, 2015

---

* Research Fellow, Auckland University of Technology, Private Bag 92006, 1142 Auckland, New Zealand. Phone: +64 9 921 9999; Fax: +64 9 921 9940; Email: adrian.fernandez@aut.ac.nz

** Professor of Finance, Auckland University of Technology; Email: bart.frijns@aut.ac.nz

*** Professor of Financial Econometrics, Cass Business School, City University, London, ECIY 8TZ, England; Tel: +44 (0)20 7040 0186 E-mail: a.fuertes@city.ac.uk.

**** Professor of Finance, EDHEC Business School, 392 Promenade des Anglais, Nice, France; Tel: +33 (0)4 9318 3255. E-mail: Joelle.Miffre@edhec.edu.

§ We acknowledge the comments from participants at the 2015 EDHEC Risk Conference in London.

1. Introduction

This article explores the relationship between total skewness and subsequent returns in commodity futures markets. It is intuitive to think that extreme levels of skewness could be driven by supply and demand shocks or by shocks to inventories. For example, double-digit growth in the BRIC countries, dramatic weather events (such as a draught or a hurricane), geopolitical instability (that could lead to an oil embargo) or an earthquake could deplete inventories, thus leading to backwardation, price rises and possibly also positive skewness in the distribution of commodity futures returns. Vice versa, a sudden fall in demand (*e.g.*, following the debacle of Lehman Brothers), exceptionally good weather, technological advances (such as the shale gas revolution) could lead to abundant inventories, contango and negative skewness.[1] Such extreme idiosyncratic shocks, or tail events would generally not be priced in a mean-variance framework. However, recent theoretical developments suggest that these potentially extreme outcomes, and in particular the asymmetry in these outcomes can be priced by investors.

We conduct a battery of time-series and cross-sectional tests that indicate that commodities with higher skewness in the recent past subsequently present lower mean excess returns. The price of skewness risk is negative and statistically significant at the 1% level and a fully collateralized portfolio that buys commodities with low total skewness and shorts commodities with high total skewness earns 8.01% a year with a *t*-statistic of 4.08. Such a performance compares favorably to that of the commodity risk factors previously documented in the literature such as a long-only equally-weighted portfolio of all commodities (*EW*) or the term structure (*TS*), momentum (*Mom*), and hedging pressure (*HP*) portfolios of, *inter alio*, Erb and Harvey (2006), Miffre and Rallis (2007), Basu and Miffre (2013) and Bakshi, Gao and Rossi (2015).

---

[1] *Backwardation* signals that commodity futures prices are likely to rise as maturity approaches. It occurs when inventories are low (Kaldor, 1939; Working, 1949; Brennan, 1958; Fama and French, 1987; Gorton, Hayashi and Rouwenhorst, 2012; Symeonidis, Prokopczuk, Brooks and Lazar, 2012), when the term structure of commodity futures prices slopes downward (Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006), when hedgers are net short and speculators are net long (Keynes, 1930; Cootner, 1960; Hirshleifer, 1988; Bessembinder, 1992; Basu and Miffre, 2013) or when contracts exhibit good past performance (Erb and Harvey, 2006; Miffre and Rallis, 2007; Dewally, Ederington and Fernando, 2013). Conversely, *contango* signals that commodity futures prices are likely to fall as maturity approaches. The signals are then reversed.

We also show that the pricing of skewness risk is robust to the specification of a model that includes commodity characteristics or commodity risk factors (such as the *EW*, *TS*, *Mom* and *HP* risk factors). Likewise, with an alpha of 6.58% and a *t*-statistic of 3.58, the performance of the low-minus-high skewness portfolio is not fully explained by a four-factor model that includes *EW*, *TS*, *Mom* and *HP*. This suggests that skewness is not merely an artifact of previously documented relationships between commodity futures returns and commodity risk factors. Rather the skewness signal captures risks beyond those embedded in the backwardation and contango phases present in commodity futures markets. These risks might relate to the preferences of agents for positively skewed assets. In equilibrium this translates into a negative price of skewness risk and in an underperformance of commodities with positively skewed return distribution.

Our article contributes to two strands of the literature. It adds to our understanding of the factors that price commodity futures by showing that skewness risk matters beyond the risks captured in Bakshi, Gao and Rossi (2015) or Basu and Miffre (2013). Our work also builds on the skewness literature by extending the results previously reported in the equity and option markets to the commodity asset class. To cite a few seminal theoretical contributions, our paper supports the conclusions of Barberis and Huang (2008) and Mitton and Vorkink (2007) that assets with positive asymmetry are in high demand and thus subsequently underperform. Our conclusion that commodities with positive skewness are more appealing and thus command a negative risk premium is also aligned with the conclusions reported in a wide range of empirical articles that study the pricing of skewness.[2]

The notion that skewness can affect asset prices has been demonstrated by several theoretical studies. These theoretical frameworks rely on the assumption of assets with so-called "lottery-like" payoff structures, i.e. assets with small probabilities of having large positive returns and combine this with investors who either have prospect theory preferences (Barberis and Huang, 2008) or with investors who have heterogeneous preferences (Mitton and Vorkink, 2007). In Barberis and Huang's (2008) theoretical framework investors have homogenous preferences based on cumulative prospect theory. Under this theory, investor have value functions that are

[2] Among the many measures of skewness that have been studied in the empirical literature, one can cite: systematic skewness (Kraus and Litzenberger, 1976; Harvey and Siddique, 2000); idiosyncratic skewness (Boyer, Mitton and Vorkink, 2010); expected idiosyncratic skewness (Boyer, Mitton and Vorkink, 2010); total skewness based on high frequency data (Amaya, Christoffersen, Jacobs and Vasquez, 2015); shock to option-implied skewness (Chang, Christoffersen and Jacobs, 2013); option-implied risk-neutral skewness (Bali and Murray, 2013; Conrad, Dittmar and Ghysels, 2013).

concave over gains, but convex over losses. This concavity in the gains domain and convexity in the loss domain, makes investors sensitive to the tails of the distribution (i.e. extreme outcomes), where their sensitivity is asymmetric, i.e. they have a strong preference to hold assets with extreme outcomes in the gains domain (i.e. lotteries), and have an aversion to holding assets with extreme outcomes in the loss domain (disasters). This leads to positively skewed assets being relatively overpriced, and negatively skewed assets being relatively underpriced. Barberis and Huang (2008) show that in their framework, these preferences lead to skewness not only being priced in portfolios of assets, but also in individual assets. In contrast to Barberis and Huang (2008), Mitton and Vorkink (2007) rely on the notion of heterogeneous preferences, where agents are either of the traditional, mean-variance optimizing, type or are of the skewness preference type. In a world where these two trader types exist, skewness ends up being priced, where assets with high skewness are in higher demand than other assets and end up being overpriced. Although both frameworks build on different assumptions, their predictions are very similar, i.e. asset with high degrees of skewness tend to be overpriced and therefore have lower expected returns than assets with low levels of skewness.

There are several studies that empirically confirm the predictions of Barber and Huang (2008) and Mitton and Vorkink (2007), specifically with regards to the pricing of assets with high or low levels of skewness. Kumar (2009), for instance, demonstrates that for a sample of US investors, individuals display a greater preference for high skewness stocks than do institutional investors, thus lending support to the idea of heterogeneous preferences of Mitton and Vorkink (2007). He also documents that those investors who invest in lottery-like stocks considerably underperform those who do not invest in lottery-like stocks. Boyer, Mitton and Vorkink (2010) perform several asset pricing tests and provide strong empirical evidence that portfolios containing stocks with low levels of skewness significantly outperform portfolios with high levels of skewness. These results are robust to various asset pricing model, and are observed both in time-series and cross-section. Similar results are obtained by Amaya et al. (2015) who implement a trading strategy based on a realized measure of skewness, and Bali and Murray (2013) who implement a trading strategy based on skewness implied from option prices.

The findings of a premium for low skewness assets and a discount for high skewness assets has not only been observed in equity markets. Boyer and Vorkink (2014) examine the relation between total skewness and stock options and document that skewness is also priced in the option market.

The empirical studies mentioned above provide strength to the theoretical notions of either markets with homogeneous cumulative prospect theory preferences, or markets with different agents, where some agents have preferences for assets with positively skewed return distributions. While skewness preference has been documented in the equity market and its derivatives, we are not aware of any study that has examined the existence of skewness preference and whether skewness is priced in commodity markets.

The remainder of the article is structured as follows. Section 2 describes the data and the commodity risk factors deemed to account for backwardation and contango. Section 3 studies the characteristics of the constituents of the skewness portfolios. Sections 4 and 5 present our time-series and cross-sectional results respectively; Section 4 focuses on the performance of a low-minus-high total skewness portfolio and Section 5 centers around the cross-sectional pricing of skewness risk. Finally, Section 6 concludes.

2. Commodity Data and Risk Factors

We use 12 agricultural commodities (cocoa, coffee C, corn, cotton n°2, frozen concentrated orange juice, oats, rough rice, soybean meal, soybean oil, soybeans, sugar n° 11, wheat), 5 energy commodities (electricity, gasoline, heating oil n° 2, light sweet crude oil, natural gas), 4 livestock commodities (feeder cattle, frozen pork bellies, lean hogs, live cattle), 5 metal commodities (copper, gold, palladium, platinum, silver), and random length lumber. The futures returns are constructed as logarithmic price differences assuming that we hold the nearest-to-maturity contract up to one month before maturity and then roll to the second nearest contract. The frequency of the price data is daily.

As pricing model, we use the three-factor model of Bakshi, Gao and Rossi (2015) that we augment with the hedging pressure factor *HP* of Basu and Miffre (2013).[3] Bakshi, Gao and Rossi (2015) use as risk factors the excess returns of three commodity portfolios: an equally-weighted monthly-rebalanced portfolio of all commodity futures (*EW*), a term structure portfolio (*TS*) and a momentum portfolio (*Mom*). The *TS*, *Mom* and *HP* risk factors are long-

[3] We obtain similar results from the use of the three-factor model of Bakshi, Gao and Rossi (2015), and from that of a four-factor model that uses the S&P-GSCI in place of EW.

short fully-collateralized portfolios of commodity futures that buy the 20% of commodities deemed to be in backwardation and short the 20% of commodities deemed to be in contango. The constituents in the long-short portfolios are equally-weighted.

For the *TS* factor, the criterion employed to sort commodities into quintiles is the average over the past 12 months of a commodity's roll-yield (measured as the time t difference in the logarithmic prices of the front and second-nearest contracts). Consequently, the *TS* factor buys/shorts the quintile with highest/lowest average roll-yields. For the *Mom* factor, the criterion upon which commodities are sorted into quintiles is the average futures return of the commodity over the past 12 months. Subsequently, the *Mom* factor buys/shorts the quintile with best/worst past performance. For the *HP* factor, the quintiles are formed based on the hedgers' and speculators' hedging pressures of each commodity averaged over the past 12 months. The latter are defined as $HP_H \equiv \frac{Long_H}{Long_H+Short_H}$ and $HP_S \equiv \frac{Long_S}{Long_S+Short_S}$, where $Long_H$ ($Long_S$) and $Short_H$ ($Short_S$) denote the open interests of long and short hedgers (speculators) for a given commodity averaged over the past 12 months. Accordingly, the *HP* portfolio buys the 20% backwardated contracts with lowest HP_H and highest HP_S values and shorts the 20% contangoed contracts with highest HP_H and lowest HP_S values. The choice of a rather long ranking period of 12 months is dictated by the fact that the *TS*, *Mom* and *HP* signals are deemed to capture the slow dynamics of inventories hypothesized by the theory of storage (Gorton, Hayashi and Rouwenhorst, 2012). Irrespective of the signal considered, we hold the positions for a month. This portfolio formation approach is conducted sequentially over the time period from January 1987 to November 2014.[4]

Table 1, Panel A presents summary statistics for the commodity factors. As previously reported (Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006 amongst many others), following a long-short approach to commodity investing is profitable: the Sharpe ratios of the long-short portfolios range from 0.39 to 0.65 versus merely -0.02 for the long-only *EW* portfolio. All long-short portfolios earn positive and statistically significant mean excess returns. Aligned with the notion that long backwardated (contangoed) positions make (lose) money, more detailed analysis reveals that the long *TS*, *Mom* and *HP* portfolios earn positive mean returns of 4.25% (t-statistic of 1.12), 7.44% (t-statistic of 1.70) and 2.30% (t-statistic of 0.60) *p.a.*, respectively, while the short *TS*, *Mom* and *HP* portfolios earn negative mean

[4] Our choice of cross-section and time-series is dictated by the availability of open interests for commercial and non-commercial participants (hedgers and speculators, respectively) in the Commitment of Traders report published by the CFTC.

returns of -5.05% (*t*-statistic of -1.36), -10.53% (*t*-statistic of -2.68) and -9.31% (*t*-statistic of -2.54) *p.a.*, respectively. Table 1, Panel B reports the correlations between the risk factors. The correlations range from 0.04 to 0.37, suggesting that none of the factors is redundant.

3. Characteristics of the Constituents of the Skewness Portfolios

At the end of each month, we measure the total skewness or the third standardized moment[5] of the returns distribution of each commodity over a ranking period of 12 months of daily data. Table 2 presents averages of the characteristics of the skewness portfolio constituents, with P1 including every month the commodities with the 20% lowest total skewness and P5 including the commodities with the 20% highest total skewness over the past 12 months. The characteristics are measured for the constituents of each quintile; they are then averaged across portfolio constituents and over time.

Three sets of characteristics are considered. The first set reported in Table 2, Panel B relates to the natural cycle of backwardation and contango present in commodity futures markets, and includes roll-yields, past performance, speculators' hedging pressure and hedgers' hedging pressure as averaged over the same 12 months as the ones used to calculate the skewness of the constituents.

The second set of characteristics reported in Table 2, Panel C includes features that are price- or return-based and that could proxy for investors' preference for gambles and positively skewed lottery-like payoffs (Kumar, 2009); in other words, these characteristics are not directly related to commodity futures pricing. These features include the average price of the commodities included in the skewness quintile, maximum and minimum returns in the same 12 months as the ones used to measure total skewness (Bali, Cakici and Whitelaw, 2011), total volatility (measured as the standard deviation of daily returns over a 12-month ranking period), idiosyncratic volatility[6] (hereafter denoted $IVol$ and measured as the standard deviation of the residuals from an OLS regression of commodity futures returns onto a four-

[5] We use the standard skewness coefficient measure $Sk = \left[\frac{1}{D}\sum_{d=1}^{D}(r_d - \mu)^3\right]/\sigma^3$ with r_d the daily return of a given commodity on day d, D is the number of days in a window of $R = 12$ months and μ and σ the mean and standard deviation of the daily returns distribution, respectively.

[6] Boyer, Mitton and Vorkink (2009) argue that agents' preference for positive-skewed lottery-like payoffs explains the underperformance of high idiosyncratic volatility stocks (Ang, Hodrick, Xing and Zhang, 2009).

factor model that includes *EW*, *TS*, *Mom* and *HP* using again daily observations over a 12-month ranking period), realized kurtosis and $open interest (measured as the product of the price of the futures contract and its open interest).

The third set of characteristics, reported in Table 2, Panel D, looks at alternative proxies of skewness. The first alternative proxy, called systematic skewness, is calculated as in Kraus and Litzenberger (1976) and Harvey and Siddique (2000) as the slope coefficient δ in the following regression $r_{it} = \alpha + \beta EW_t + \delta EW_t^2 + \varepsilon_t$, where r_{it} is a commodity excess returns sampled at a daily frequency over the 12-month period used to calculate total realized skewness and EW_t is treated as a valid proxy of the market portfolio in the present context. The second alternative measure of skewness, called idiosyncratic skewness and denoted iSk hereafter, is measured in the spirit of Boyer, Mitton and Vorkink (2010) as the skewness of the residuals from a four-factor model that includes *EW*, *TS*, *Mom* and *HP*.[7] The third alternative proxy for skewness, called expected idiosyncratic skewness and denoted $E_t(iSk_{it+1})$ hereafter, follows Boyer, Mitton and Vorkink (2010) and is estimated first by running the following cross-sectional regressions at the end of each month t

$$iSk_{it} = \beta_{0t} + \beta_{1t} iSk_{it-1} + \beta_{2t} Z_{it-1} + \upsilon_{it}$$

Z_{t-1} is a vector of commodity specific control variables measured over the same 12 months of daily data as the ones used to measure iSk_{it-1}; Z_{it-1} includes each commodity's idiosyncratic volatility, $open interest, average roll yield, past performance and average speculators' hedging pressure. We then use the estimated parameters and information on Z_{it} as observed at the end of month t to obtain an estimate of each commodity's expected idiosyncratic skewness; namely, $E_t(iSk_{it+1}) = \hat{\beta}_{0t} + \hat{\beta}_{1t} iSk_{it} + \hat{\beta}_{2t} Z_{it}$. We expect total skewness, systematic skewness, idiosyncratic skewness and expected idiosyncratic skewness to be highly correlated of course but we nonetheless include all four skewness proxies in our analysis to test which signal, if any, is the best at pricing commodity futures.

Table 2, Panel A shows that the average realized total skewness ranges from -0.73 to 0.54 with a spread that is significant at the 1% level. Panel B indicates that commodity futures with

---

[7] From the perspective of a well-diversified investor, idiosyncratic skewness should not matter (Kraus and Litzenberger, 1976; Harvey and Siddique, 2000); yet, recent evidence by Mitton and Vorkink (2007) and Barberis and Huang (2008) suggest that it is relevant to the pricing of stock returns.

negative asymmetry (P1) tend to present backwardated characteristics inasmuch as they have on average higher roll-yields, better past performance, lower hedgers' hedging pressure and higher speculators' hedging pressure than their highly skewed counterparts (P5). As indicated by the *t*-statistics for the differences in column 6, the backwardation and contango characteristics of the constituents of P1 are found to be statistically different from those obtained for the constituents of P5. This indicates that total skewness could be related to hedging pressure and inventories, and thus to the demand for and the supply of commodities; we will study this possibility below.

Table 2, Panel C shows that commodities with extreme skewness (P1 and P5) tend to present higher levels of total volatility, higher levels of idiosyncratic volatility and higher levels of kurtosis than portfolios with intermediate levels of skewness (P2 to P4). This is somehow expected as extreme levels of skewness should be associated with higher volatility. Panel C also reports that higher total skewness (and thus lottery-like payoffs) comes hand-in-hand with lower prices (Kumar, 2009), higher idiosyncratic volatility (Boyer, Mitton and Vorkink, 2009). Finally Table 2, Panel D shows that lower/higher total skewness is associated with lower/higher systematic skewness, lower/higher idiosyncratic skewness and lower/higher expected idiosyncratic skewness. As there is a positive relation between all four skewness measures, it is important to find out which of these alternative skewness signals is best at pricing commodity futures. This in part is the focus of Section 4.

4. Time-Series Properties of the Skewness Portfolios

4.1. Baseline Results

This section studies the time-series properties between the total skewness of commodity futures and their subsequent returns. At the end of each month, commodities are sorted into quintiles based on their realized total skewness measured over a ranking period of $R = 12$ months of daily data. We hold the various portfolios for a month, at which time the same process is repeated until the sample ends. Table 3 presents summary statistics for the performance of the skewness-sorted portfolios with the first column summarizing the results for the assets with the lowest asymmetry (P1) and the fifth column presenting the results for the assets with the highest asymmetry (P5). We also construct a fully-collateralized low-minus-high portfolio that buys P1 and shorts P5 (*e.g.*, Boyer, Mitton and Vorkink, 2010; Amaya, Christoffersen, Jacobs and Vasquez, 2015).

The results of Table 3, Panel A indicate that the theoretical negative relationship between past total skewness and subsequent returns identified in Mitton and Vorkink (2007) or in Barberis and Huang (2008) extends to commodity futures markets. P1 earns a positive mean excess return of 5.12% a year (*t*-statistic of 1.52), while P5 earns a negative mean excess return of -10.89% a year (*t*-statistic of -3.54). Mean returns are found to monotonically decrease as total skewness increases. Systematically taking (fully-collateralized) long positions in low-skewness commodities and short positions in high-skewness commodities yields a positive and statistically significant mean excess return equal to 8.01% a year with an associated *t*-statistic of 4.08. The performance of the long-short portfolio is more driven by the underperformance of the highly skewed assets than by the outperformance of the lowly skewed assets. This suggests that the results are more driven by the preference of agents for positive skewness than by their aversion for negative skewness. Unlike the P1 to P5 portfolios, the low-minus-high skewness portfolio P1-P5 presents a positive skew and low levels of risk (low total volatility, low 99% value-at-risk and low maximum drawdown). In terms of risk-adjusted performance, P1-P5 yields a Sharpe ratio at 0.79, which is higher than the Sharpe ratios obtained for the commodity risk factors in Table 1.[8]

We further appraise risk-adjusted performance by means of the portfolio's alpha relative to a four-factor model that includes *EW*, *TS*, *Mom* and *HP*. Table 3, Panel B presents the coefficients estimated from such regressions for each of the skewness-sorted portfolios P1 to P5, as well as for the low-minus-high P1-P5 portfolio. Aligned with the evidence presented in Table 2, Panel B, P1 presents higher loadings on the *TS* and *HP* risk factors than P5, suggesting that commodity futures with lower asymmetry present backwardated characteristics, while commodity futures with higher asymmetry tend to be in contango. However, even after accounting for the natural backwardation and contango cycles, the portfolio P1 made of lowly skewed commodities performs well with an alpha at 4.28% a year (*t*-statistic of 1.79), the portfolio P5 made of highly skewed commodities performs remarkably poorly with an alpha of -8.89% a year (*t*-statistic of -3.96) with the performance across quintiles decreasing monotonically as skewness increases. As a result, the performance of the low-minus-high P1-P5 portfolio is quite remarkable at 6.58% a year with an associated

[8] We carry out a similar experiment sorting the commodities into quintiles based on their 12-month realized kurtosis, in place of their 12-month realized skewness. High kurtosis commodities were not found to perform better than low kurtosis commodities, suggesting that the 4th moment of the distribution of commodity futures returns has no impact on pricing.

t-statistic of 3.58. Thus, even though the performance of the skewness-sorted portfolio somehow relates to the natural propensity of commodity futures markets to be backwardated or contangoed, the effect of skewness is not fully captured by standard commodity pricing models: the skewness signal captures risks beyond those embedded in the backwardation and contango phases. These results fit well in a large literature that establishes that investors' preference for lottery-like payoffs explain the subsequent underperformance of positively skewed assets (Mitton and Vorkink, 2007; Barberis and Huang, 2008; Kumar, 2009; Amaya, Christoffersen, Jacobs and Vasquez, 2015, to name a few).

4.2. Robustness Analysis

Table 4 tests the robustness of the performance of the P1-P5 portfolio to various specifications of the methodology employed (Panels A to C), to liquidity and transaction costs considerations (Panel D) and to the samples analyzed (Panel E).

Table 4, Panels A and B test the robustness of the performance of the low-minus-high total skewness portfolio to the ranking period employed to measure the skewness of each asset (Panel A) and to the holding period of the P1-P5 portfolios (Panel B). Irrespective of the ranking and holding periods considered, the long P1 - short P5 portfolios perform rather well, suggesting that our main conclusion of a negative relationship between total skewness and returns holds in these various settings too. Unless specified otherwise, the remainder of the article sets the ranking and holding periods to the base cases of $R = 12$ and $H = 1$ months.

Table 4, Panel C tests the robustness of our results to the specification of the skewness signal. Instead of using total skewness as before, we now use as sorting signals each asset's systematic skewness, idiosyncratic skewness and expected idiosyncratic skewness. The low-minus-high portfolio based on idiosyncratic skewness offers 6.53% a year or 1.47% less than the low-minus-high portfolio based on total skewness in Table 3. The P1-P5 portfolios based on systematic skewness or expected idiosyncratic skewness present risk-adjusted performance measures that are negligible compared to those reported in Table 3 for total skewness. We conclude thus that total skewness is the risk factor that matters the most in terms of pricing.

As a further robustness check, we address possible concerns over lack of liquidity by redeploying the strategies, systematically excluding the 10% of commodities with the lowest average open interest over the 12 months preceding portfolio formation. The results reported in the first row of Table 4, Panel D demonstrate that the P1-P5 strategy still works well when illiquid assets are omitted and thus that the performance reported in Table 3 is not a mere compensation for lack of liquidity. Table 4, Panel D also tests the impact that transaction costs may have on the profitability of the strategies. Relative to Locke and Venkatesh (1997), we are conservative in setting transaction costs at 0.033% and at twice that amount (0.066%). The results presented in the second and third rows of Panel D show that the skewness strategy is cheap to implement and profitable net of transaction costs. Finally, the last row of Panel D presents the level of transaction costs that would make the skewness strategy break-even. That level is estimated at 0.933 per round-trip transaction, an estimate that by far exceeds the conservative measure of Locke and Venkatesh (1997). These evidence indicate that the performance of the low-minus-high skewness portfolio is not merely an illiquidity premium or a reward for transaction costs.

Finally, Panel E summarizes the performance of the P1-P5 strategies over *i*) two sub-periods of roughly equal length (January 1987-May 2001 and June 2001-November 2014), *ii*) two sub-periods, respectively, preceding and reflecting the financialization of commodity futures markets dated January 2006 as suggested, *e.g.* in Stoll and Whaley (2010) and *iii)* two sub-periods, respectively, preceding and reflecting the late 2000s financial crisis using July 2007 as approximate date, see *e.g.*, Brunnermeier (2009). The results are found to be more or less robust: the performance of P1-P5 does not seem to be sample-specific.

In summary, we conclude that the time-series properties of the skewness portfolios are robust to various methodological specifications, transaction costs, illiquidity concerns and sub-samples. Buying lowly skewed assets and shorting highly skewed assets is a source of abnormal performance in commodity futures markets. This result is aligned with a wide-ranging equity literature that also argues for a negative relationship between past skewness and future stock returns (Barberis and Huang, 2008; Boyer, Mitton and Vorkink, 2010; Amaya, Christoffersen, Jacobs and Vasquez, 2015, among others).

5. Cross-Sectional Approach

5.1. Methodology

This section tests whether skewness explains the cross-sectional variations in commodity futures returns. To this end, we follow various approaches starting with simple cross-sectional regressions of monthly commodity futures returns onto realized skewness Sk_{it} measured over a ranking period of $R = 12$ months of daily data.

$$r_{it+1} = \lambda_{0t+1} + \lambda_{Skt+1} Sk_{it} + v_{it+1} \tag{1}$$

where r_{it+1} is the return on the i^{th} commodity futures contract in month $t+1$ and v_{it+1} is a random error term. This regression is used reiteratively each month until the end of the sample and ultimately produces one vector of prices of risk for skewness λ_{Skt+1}. The statistical significance of λ_{Skt+1} is then tested after adjusting the standard errors for first-order serial correlation and heteroscedasticity using Newey and West (1987).

We also augment equation (1) with the commodity characteristics Z_{it} presented in Table 2, where the commodity characteristics are averaged over the same sample as the one used to calculate Sk_{it}.[9] The cross-sectional regression (1) then becomes

$$r_{it+1} = \lambda_{0t+1} + \lambda_{Skt+1} Sk_{it} + \lambda_{Zt+1} Z_{it} + v_{it+1} \tag{2}$$

This regression enables us to disentangle the impact of skewness from that of commodity characteristics on the pricing of commodity futures. Again a Newey and West (1987) correction is used to test the statistical significance of λ_{Skt+1} and λ_{Zt+1}.

To ascertain that skewness is not an artifact of previously documented relationships between commodity futures returns and commodity risk factors (*e.g.*, Basu and Miffre, 2013; Bakshi, Gao and Rossi, 2015), we also employ a variant of the two-step approach of Fama and MacBeth (1973) as deployed by Ang, Hodrick, Xing and Zhang (2009) in the context of idiosyncratic volatility. The cross-sectional regression (2) then becomes

$$r_{it+1} = \lambda_{0t+1} + \lambda_{Skt+1} Sk_{it} + \lambda_{Ft+1} \hat{\beta}_{it+1} + v_{it+1} \tag{3}$$

$\hat{\beta}_{it+1}$ is a vector of $K = 4$ OLS sensitivities of commodity futures returns to the four-factor model that includes *EW*, *TS*, *Mom* and *HP*. As in Ang, Hodrick, Xing and Zhang (2009), the sensitivities are estimated using daily information within the month $t+1$; *i.e.*, $\hat{\beta}_{it+1}$ and r_{it+1} are contemporaneous. The statistical significance of the resulting prices of risk λ_{Skt+1} and λ_{Ft+1} is then tested using Shanken (1992) correction. Stated differently, the question we are

[9] To address possible concerns over multicollinearity, we omit from the cross-sectional regressions five characteristics that are highly correlated with total skewness. These include: systematic skewness, idiosyncratic skewness, expected idiosyncratic skewness, maximum and minimum returns in the previous 12 months.

asking via equations (2) and (3) is the following: Is skewness still priced when commodity characteristics and commodity risk factors are factored in the pricing model?

5.2. Baseline Results

Table 5 presents the average of the cross-sectional prices of risk, *t*-statistics and adjusted-R^2 as obtained from equations (1) to (3). In line with the equity literature (Barberis and Huang, 2008; Mitton and Vorkink, 2007, among others), skewness is found to be negatively priced in commodity futures markets: other things being equal, commodities with positive (negative) skewness in the recent past earn negative (positive) excess returns in the near future. For example, in model (1), the estimated coefficient for total skewness equals -0.0087 with a Newey-West *t*-statistic of -4.03. The significance of λ_{Sk} drops when commodity characteristics and commodity risk factors are included in the cross-sectional regressions, suggesting that the control variables and risk factors employed might be somehow overlapping with skewness. However, the estimates of λ_{Sk} are found to be reliably negative across models with associated Newey and West or Shanken *t*-statistics at most equal to -3.27.

Some of the control variables employed to proxy for the pricing of commodity futures attract the correct signs; *e.g.*, better past performance in models (2) and (4) comes hand-in-hand with higher commodity futures returns as hypothesized by the theories of storage and hedging pressure. Likewise, commodities with higher sensitivities to the *Mom* and *HP* factors are found to command higher mean returns cross-sectionally in models (5) and (6); this is again what the hedging pressure hypothesis predicts. In support of the conclusions of Boyer, Mitton and Vorkink (2009), Table 5, as Table 2 beforehand, shows that, other things being equal, commodity futures with more positive asymmetry presents lower mean returns and higher idiosyncratic volatility, suggesting that the idiosyncratic volatility puzzle could relate to the preference of agents for assets with positively skewed distribution. Aligned with Ang, Hodrick, Xing and Zhang (2009) for equities and Fernandez-Perez, Fuertes and Miffre (2015) for commodities, we observe in model (3) a negative relationship between past idiosyncratic volatility and subsequent mean returns within a model that fails to recognize the natural cycles of backwardation and contango present in commodity futures markets. This negative relationship disappears when past performance is included as control variable in model (4), suggesting that idiosyncratic volatility might be a proxy for a missing factor relating to backwardation and contango.

The results of Table 5 also indicate that characteristics such as average roll-yield, hedgers' and speculators' hedging pressures, kurtosis, average past prices have no role to play in explaining cross-sectional returns. Likewise, the risks associated with the *EW* and *TS* factors are not priced cross-sectionally. Relative to the commodity pricing literature, it is interesting to note that skewness risk commands a premium that is statistically more significant than the premiums obtained from the four-factor model based on *EW*, *TS*, *Mom* and *HP*. Out of all the models considered, the four-factor model augmented with skewness has the highest explanatory power (26.8%). Adding total skewness to the traditional four-factor model seems important.

5.3. Robustness Checks

Table 6 checks the robustness of the cross-sectional results to the choices of ranking periods used to measure the skewness signal (Panel A), asset pricing model (Panel B), definition of skewness (Panel C) and sub-samples (Panel D). For the sake of concision, we only report the prices of skewness risk λ_{Sk} estimated from models (4) and (5) of Table 5, alongside *t*-statistics corrected using Newey and West (1987) or Shanken (1992), respectively. So most of the forthcoming analysis is based on two models, one that includes commodity characteristics and another one that includes commodity risk factors.

Broadly speaking, the conclusions are unchanged: commodities with lower skewness in the recent past earn higher returns one month ahead. For example, the inference holds for most ranking periods considered (Table 6, Panel A) even though the signal seems to be stronger over shorter ranking periods.

The use of alternative pricing models emanating from the literature on traditional assets such as the four-factor model of Carhart (1997) or version thereof augmented with *EW*, *TS*, *Mom*, *HP* and Barclays bond index does not alter our conclusion either. If anything, omitting the risk factors that are commodity-specific tend to overstate the negative relationship between realized skewness and mean returns and to magnify the statistical significance of λ_{Sk}.

Table 6, Panel C studies the cross-sectional relationship between alternative definitions of skewness and commodity futures returns. The alternative measures of skewness considered are systematic skewness, idiosyncratic skewness and expected idiosyncratic skewness as defined in Section 3. The results suggest that systematic skewness is not priced in commodity markets; the conclusion on the pricing of expected idiosyncratic skewness seems model-specific; the inference regarding the pricing of idiosyncratic skewness is aligned with the results obtained for total skewness (Table 5, model (5)), suggesting that it is hard to disentangle the two signals. Altogether, the skewness of futures returns, alongside idiosyncratic skewness, are found to be important in terms of pricing.

Finally Table 6, Panel D confirms that the cross-sectional results obtained in Table 5 are not sample-specific. The evidence are found to be stronger over the earlier parts of the sample and weaker afterwards. But overall, the results seem to suggest that the relationship between realized skewness and forthcoming futures returns is negative over most sub-periods.

6. Conclusions

This article contributes to the literature on commodity futures pricing by showing that total skewness matters to the pricing of commodity futures. Both time-series and cross-sectional tests indicate that commodities with higher skewness in the recent past subsequently exhibit lower mean returns. For example, we show that the price of skewness risk is negative and statistically significant at the 1% level and that a portfolio that buys commodities with low realized skewness and shorts commodities with high realized skewness earns 8.01% a year with a *t*-statistic of 4.08. Such a performance compares favorably to that of commodity risk factors previously documented in the literature such as a long-only equally-weighted portfolio of all commodities (*EW*) or the term structure (*TS*), momentum (*Mom*) and hedging pressure (*HP*) portfolios of, *inter alios*, Erb and Harvey (2006), Miffre and Rallis (2007), Basu and Miffre (2013) and Bakshi, Gao and Rossi (2015). We note also that out of all skewness signals considered, total realized skewness is probably the most preeminent at pricing commodities and that our results are robust to several choices of ranking and holding periods, across sample periods and are not driven by liquidity or transaction costs considerations.

Finally we show that negatively skewed commodities present backwardated characteristics such as higher roll-yields, better past performance, lower hedgers' hedging pressures and higher speculators' hedging pressures. Vice versa, positively skewed commodities tend to be in contango. This highlights the link between skewness on the one hand and inventories, supply and demand on the other hand. Yet, the pricing of skewness is found to be robust to the specification of a pricing model that includes commodity characteristics or commodity risk factors. Likewise, with an alpha of 6.58% and a *t*-statistic of 3.58, the performance of the low-minus-high skewness portfolio is not fully explained by a four-factor model that includes

EW, *TS*, *Mom* and *HP*. This suggests that skewness is not merely an artifact of previously documented relationships between commodity futures returns and commodity risk factors. Namely, the skewness signal captures risks beyond those embedded in the backwardation and contango phases present in commodity futures markets. These risks might relate to the preferences of agents for positively skewed assets as in Barberis and Huang (2008). In equilibrium this translates into a negative price of skewness risk.

References

Amaya, D., Christoffersen, P., Jacobs, K., and A. Vasquez. (2015). Does realized skewness predict the cross-section of equity returns? Unpublished Working Paper, UQAM University.

Ang, A., R. J. Hodrick, Y. Xing, X. Zhang. (2009). High idiosyncratic volatility and low returns: International and further U.S. evidence, *Journal of Financial Economics* 91, 1–23.

Bakshi, G., Gao, X., and Rossi, A. (2015). A better specified asset pricing model to explain the cross-section and time-series of commodity returns. Unpublished Working Paper, University of Maryland.

Bali, T.G., Caciki, N., and R.F. Whitelaw. (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns, *Journal of Financial Economics* 99, 427–446

Bali, T.G., and Murray. (2013). Does risk-neutral skewness predict the cross section of equity option portfolio returns?, *Journal of Financial and Quantitative Analysis* 48, 1145-1171.

Barberis, N., and M. Huang. (2008). Stocks as lotteries: The Implications of probability weighting for security prices. *American Economic Review* 98, 2066–2100.

Basu, D., and J. Miffre. (2013). Capturing the risk premium of commodity futures: The role of hedging pressure, *Journal of Banking and Finance* 37, 2652-2664.

Bessembinder, H. (1992). Systematic risk, hedging pressure, and risk premiums in futures markets, *Review of Financial Studies* 5, 637-667.

Boyer, B., Mitton, T., and K. Vorkink. (2010). Expected idiosyncratic skewness, *Review of Financial Studies* 23, 169-202.

Brennan, M. (1958) The supply of storage, *American Economic Review* 48, 50-72.

Brunnermeier, M. (2009). Deciphering the liquidity and credit crunch 2007-2008. *Journal of Economic Perspectives*, 23, 77-100.

Carhart, M. (1997). On persistence of mutual fund performance. *Journal of Finance* 52, 57-82.

Chang, B.Y., Christoffersen, P., and K. Jacobs. (2013). Market skewness risk and the cross section of stock returns, *Journal of Financial Economics* 107, 46–68.

Conrad, J., Dittmar, R., and E. Ghysels. (2012). Ex-ante skewness and expected stock returns, *Journal of Finance* 68, 85-124.

Cootner, P. (1960). Returns to speculators: Telser vs. Keynes. *Journal of Political Economy* 68, 396–404.

Dewally, M., L., Ederington, and C., Fernando. (2013). Determinants of trader profits in commodity futures markets. *Review of Financial Studies* 26, 2648-2683.

Erb, C., and C. Harvey. (2006). The strategic and tactical value of commodity futures, *Financial Analysts Journal* 62, 69-97.

Fama, E. F., and J. D. MacBeth. (1973). Risk, returns, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607-636.

Fama, E., and French, K. (1987). Commodity futures prices: Some evidence on forecast power, premiums, and the theory of storage, *Journal of Business* 60, 55-73.

Fernandez-Perez, A., A-M., Fuertes and J. Miffre. (2015). Is idiosyncratic volatility priced in commodity futures markets?, Unpublished Working Paper, Cass Business School.

Gorton, G., Hayashi, F., and G. Rouwenhorst. (2012). The fundamentals of commodity futures returns, *Review of Finance* 17, 35-105.

Gorton, G., and G. Rouwenhorst. (2006). Facts and fantasies about commodity futures, *Financial Analysts Journal* 62, 47-68.

Harvey, C. R., and A. Siddique. (2000). Conditional skewness in asset pricing tests, *Journal of Finance* 55, 1263– 95.

Hirshleifer, D. (1988). Residual risk, trading costs, and commodity futures risk premia, *Review of Financial Studies*, 1, 173-193.

Kaldor, N. (1939) Speculation and economic stability, *Review of Economic Studies* 7, 1-27.

Keynes, M. (1930). A treatise on money, II: The applied theory of money. Edition Macmillan and Co.

Kraus, A., and R. H. Litzenberger. (1976). Skewness preference and the valuation of risky assets, *Journal of Finance* 31, 1085–100.

Kumar, A. (2009). Who gambles in the stock market?, *Journal of Finance* 64, 1889-1933.

Locke, P., and P. Venkatesh. (1997). Futures market transaction costs, *Journal of Futures Markets* 17, 229-245.

Miffre, J., and G. Rallis. (2007). Momentum strategies in commodity futures markets, *Journal of Banking and Finance* 31, 6, 1863-1886.

Mitton, T., and K. Vorkink. (2007). Equilibrium underdiversification and the preference for skewness, *Review of Financial Studies* 20, 1255-1288.

Newey, W. K., and West, K. D. (1987) Hypothesis testing with efficient method of moments estimation, *International Economic Review* 28, 777-787.

Shanken, J. (1992). On the estimation of beta-pricing models, *Review of Financial Studies* 5, 1–33.

Stoll, H., and R. Whaley. (2010). Commodity index investing and commodity futures prices, *Journal of Applied Finance* 20, 7–46.

Symeonidis, L., Prokopczuk, M., Brooks, C. and Lazar, E. (2012). Futures basis, inventory and commodity price volatility: An empirical analysis, *Economic Modelling* 29, 2651-2663.

Working, H. (1949). The theory of price of storage, *American Economic Review* 39, 1254-1262.

Table 1. Summary statistics for risk factors

The table presents summary statistics for the commodity risk factors sampled at daily frequency from January 1987 to November 2014. Conventional significance *t*-ratios are reported in parentheses. Sharpe ratios (SR) are annualized mean excess returns (Mean) divided by annualized standard deviations (StDev). *EW*, *TS*, *Mom* and *HP* stand for the excess returns of a long-only equally-weighted portfolio of all commodities and long-short portfolios based on term structure, momentum and hedging pressure signals, respectively. *p*-values for the significance of the correlations are reported in brackets.

Panel A: Summary statistics

	Mean		**StDev**	**SR**
Equally-weighted long-only portfolio (EW)	-0.0021	(-0.10)	0.1144	-0.0185
Term structure (TS)	0.0465	(2.05)	0.1195	0.3892
Momentum (Mom)	0.0899	(3.43)	0.1381	0.6507
Hedging pressure (HP)	0.0581	(2.63)	0.1162	0.4996

Panel B: Correlation matrix

	EW	TS	Mom
TS	0.04		
	[0.00]		
Mom	0.11	0.37	
	[0.00]	[0.00]	
HP	0.08	0.11	0.30
	[0.00]	[0.00]	[0.00]

Table 2. Characteristics of the skewness-sorted portfolios

The table presents averages of the characteristics of the skewness portfolio constituents, with P1 including every month the commodities with the 20% lowest skewness and P5 including the commodities with the 20% highest skewness over a ranking period of 12 months. The characteristics are measured for the constituents of each quintile over the same 12-month ranking periods as the ones used to measure total skewness. These characteristics are then averaged across portfolio constituents and over time. Total volatility is measured as the standard deviation of daily returns, idiosyncratic volatility is measured as the standard deviation of the residuals from an OLS regression of commodity futures returns onto a four-factor model that includes *EW*, *TS*, *Mom* and *HP*, idiosyncratic skewness is calculated as the skewness of the residuals from the same four-factor model, systematic skewness is calculated as in as the slope coefficient δ in the following regression $r_{it} = \alpha + \beta EW_t + \delta EW_t^2 + \varepsilon_t$ expected idiosyncratic skewness is measured as in Section 3, and $open interest is measured as the product of the price of the futures contract and its open interest. The last column labelled P1-P5 reports *t*-statistics of the null hypothesis that the mean of a given characteristic of P1 equals that of P5. Bold fonts indicate significance at the 10% level or better. The sample covers the period January 1987 – November 2014.

Portfolios	P1	P2	P3	P4	P5	P1-P5
Panel A: Total skewness	-0.7294	-0.2596	-0.0707	0.0978	0.5407	(-39.06)
Panel B: Backwardation versus contango characteristics						
Roll-yield	-0.0008	-0.0034	-0.0060	-0.0094	-0.0105	(10.61)
Past performance (p.a.)	2.91%	0.57%	0.78%	-1.90%	-1.86%	(3.13)
Hedgers hedging pressure	0.3969	0.4295	0.4389	0.4417	0.4531	(-13.59)
Speculators hedging pressure	0.6570	0.6387	0.6198	0.5974	0.5848	(10.38)
Panel C: Price and return based characteristics						
Price	336.80	273.41	220.98	233.77	267.37	(4.11)
Max(daily return)	0.0524	0.0506	0.0519	0.0559	0.0762	(-17.06)
Min(daily return)	-0.0847	-0.0594	-0.0542	-0.0511	-0.0534	(-15.34)
Total volatility (p.a.)	27.69%	25.92%	26.01%	26.40%	27.37%	(0.72)
Idiosyncratic volatility (p.a.)	21.55%	20.66%	21.07%	21.46%	22.71%	(-4.05)
Total kurtosis	6.8199	4.3342	3.9958	3.9872	6.4073	(1.23)
Average $ open interest (×1,000)	414,337	361,094	311,885	233,105	289,278	(3.56)
Panel D: Alternative measures of skewness						
Systematic skewness	-13.5933	-2.5238	1.8610	4.0112	11.7477	(-24.77)
Idiosyncratic skewness	-0.3552	-0.1068	-0.0049	0.0902	0.3842	(-42.16)
Expected idiosyncratic skewness	-0.0692	-0.0162	0.0066	0.0191	0.0607	(-7.00)

Table 3. Time-series properties of skewness-sorted portfolios

Panel A presents summary statistics for the performance of skewness-sorted portfolios, with P1 including the commodities with the 20% lowest total skewness and P5 including the commodities with the 20% highest total skewness over a ranking period of 12 months. P1-P5 denotes a low-minus-high skewness portfolio. Sharpe ratios are annualized mean excess returns (Mean) divided by annualized standard deviations (StDev). Panel B presents estimated coefficients and associated Newey-West *t*-statistics (in parentheses) from regressions of the excess returns of skewness-sorted portfolios on a four-factor model based on *EW*, *TS*, *Mom* and *HP*. *EW*, *TS*, *Mom* and *HP* stand for the excess returns of a long-only equally-weighted portfolio of all commodities and long-short portfolios based on term structure, momentum and hedging pressure signals, respectively. Bold fonts indicate significance at the 10% level or better. The sample covers the period January 1987 – November 2014.

Portfolios	**P1**	**P2**	**P3**	**P4**	**P5**	**P1-P5**
Panel A: Summary statistics						
Mean	0.0512	0.0401	-0.0020	-0.0277	**-0.1089**	**0.0801**
	(1.52)	(1.19)	(-0.06)	(-0.87)	(-3.54)	(4.08)
StDev	0.1748	0.1755	0.1715	0.1647	0.1596	0.1020
Sharpe ratio	0.2932	0.2287	-0.0114	-0.1683	-0.6820	0.7848
Skewness	0.0090	**-0.7888**	**-0.2246**	**-0.5818**	-0.1563	**0.2874**
	(0.07)	(-5.80)	(-1.65)	(-4.28)	(-1.15)	(2.11)
Excess kurtosis	**1.3891**	**3.1699**	**0.9979**	**2.7427**	**1.0168**	**1.1646**
	(5.10)	(11.65)	(3.67)	(10.08)	(3.74)	(4.28)
99% VaR (Cornish-Fisher)	0.1291	0.1696	0.1341	0.1577	0.1321	0.0627
% of positive months	0.5525	0.5556	0.4846	0.5062	0.4105	0.5926
Maximum drawdown	-0.4244	-0.6006	-0.7300	-0.8205	-0.9731	-0.2973
Panel B: Regression analysis						
α	**0.0428**	**0.0410**	0.0134	-0.0174	**-0.0889**	**0.0658**
	(1.79)	(1.93)	(0.67)	(-0.80)	(-3.96)	(3.58)
β (EW)	**0.9571**	**1.0502**	**1.0427**	**1.0283**	**0.8949**	0.0311
	(13.12)	(15.05)	(19.31)	(13.80)	(14.55)	(0.66)
β (TS)	**0.1951**	**0.2375**	-0.0933	**-0.1096**	**-0.1645**	**0.1798**
	(2.27)	(3.69)	(-1.45)	(-1.66)	(-2.31)	(2.74)
β (Mom)	0.0334	**-0.0894**	0.0037	0.0048	0.0293	0.0021
	(0.47)	(-1.78)	(0.07)	(0.09)	(0.48)	(0.04)
β (HP)	0.0786	**0.0806**	-0.0606	0.0341	**-0.1439**	0.1113
	(0.93)	(1.65)	(-0.98)	(0.54)	(-1.75)	(1.46)
Adjusted R-square	49.12%	56.57%	52.79%	56.87%	45.21%	5.66%

Table 4. Robustness of time-series tests

Table 4 tests the robustness of the performance of the low-minus-high skewness portfolio to various specifications of the methodology employed (Panels A to C), to liquidity and transaction costs considerations (Panel D) and to the samples analyzed (Panel E). Mean is the annualized mean excess returns of the P1-P5 fully-collateralized portfolio, StDev is the annualized standard deviation of its returns, SR stands for the Sharpe ratio, α is the annualized abnormal performance of the low-minus-high portfolio, measured as the intercept from a regression of the portfolio excess returns onto a four-factor model that includes *EW*, *TS*, *Mom* and *HP*. *R* is the ranking period over which the skewness signal is measured, *H* is the holding period over which the P1-P5 portfolio is held (both expressed in months). Newey-West *t*-statistics for the alphas are reported in parentheses. Bold fonts indicate significance at the 10% level or better. Unless specified otherwise, the sample covers the period January 1987 – November 2014.

	Mean		**StDev**	**SR**	**α**	
Panel A: Choice of ranking periods (H=1)						
R = 6	**0.0556**	(2.94)	0.0991	0.5615	**0.0479**	(2.57)
R = 12	**0.0801**	(4.08)	0.1020	0.7848	**0.0658**	(3.58)
R = 36	**0.0516**	(2.48)	0.1041	0.4959	**0.0388**	(1.66)
R = 60	**0.0591**	(2.46)	0.1149	0.5140	**0.0474**	(2.00)
R = 96	**0.0649**	(2.52)	0.1153	0.5632	**0.0533**	(1.93)
Average	0.0623		0.1071	0.5839	0.0506	
Panel B: Choice of holding periods (R=12)						
H=1	**0.0801**	(4.08)	0.1020	0.7848	**0.0658**	(3.58)
H=3	**0.0828**	(4.21)	0.1022	0.8100	**0.0618**	(3.16)
H=6	**0.0616**	(3.13)	0.1023	0.6022	**0.0424**	(2.03)
H=12	**0.0514**	(2.63)	0.1015	0.5065	0.0278	(1.51)
Average	0.0690		0.1020	0.6759	0.0495	
Panel C: Choice of sorting signal						
Systematic skewness	0.0183	(0.83)	0.1150	0.1591	0.0112	(0.48)
Idiosyncratic skewness	**0.0653**	(3.64)	0.0931	0.7017	**0.0626**	(3.46)
Expected idiosyncratic skewness	0.0241	(1.25)	0.0984	0.2453	0.0196	(1.03)
Panel D: Lack of liquidity and transaction costs						
90% most liquid contracts	**0.0631**	(3.30)	0.0992	0.6364	**0.0504**	(2.61)
T-costs = 0.033%	**0.0783**	(3.99)	0.1020	0.7680	**0.0641**	(3.49)
T-costs = 0.066%	**0.0766**	(3.90)	0.1020	0.7512	**0.0624**	(3.40)
Break-even transaction costs	0.9330					
Panel E: Sub-sample analysis						
Jan 1987-May 2001	**0.0705**	(2.51)	0.1032	0.6837	**0.0534**	(2.02)
June 2001-Nov 2014	**0.0896**	(3.26)	0.1010	0.8864	**0.0683**	(2.63)
Jan 1987-Dec 2005	**0.0774**	(3.10)	0.1062	0.7289	**0.0712**	(2.89)
Jan 2006-Nov 2014	**0.0855**	(2.73)	0.0935	0.9145	**0.0372**	(1.94)
Jan 1987-July 2007	**0.0767**	(3.25)	0.1047	0.7329	**0.0698**	(3.00)
Aug 2007-Nov 2014	**0.0890**	(2.54)	0.0950	0.9370	0.0290	(1.33)

Table 5. Cross-sectional pricing of skewness

The table reports the prices of risk associated with total skewness, commodity characteristics and commodity risk factors. *t*-statistics are reported in parentheses adjusted using corrections based on Newey-West (1987) in models (1) to (4) or Shanken (1992) in models (5) and (6). *EW*, *TS*, *Mom* and *HP* refer to the prices of risk associated with the excess returns of the long-only equally-weighted portfolio of all commodities and long-short commodity portfolios based on term structure, momentum and hedging pressure signals, respectively. Bold fonts indicate significance at the 10% level or better. The sample covers the period January 1987 – November 2014.

	(1)	**(2A)**	**(2B)**	**(2C)**	**(3)**	**(4)**	**(5)**	**(6)**
Intercept	-0.0013	0.0034	-0.0050	-0.0028	0.0063	0.0008	**-0.0033**	-0.0020
	(-0.57)	(0.56)	(-0.79)	(-0.22)	(1.17)	(0.21)	(-1.80)	(-1.12)
Skewness	**-0.0087**	**-0.0087**	**-0.0095**	**-0.0091**	**-0.0101**	**-0.0087**	**-0.0086**	
	(-4.03)	(-3.52)	(-4.26)	(-3.59)	(-3.27)	(-3.95)	(-3.53)	
Commodity characteristics								
Roll-yield		0.0360	0.0417	0.0491				
		(0.48)	(0.59)	(0.67)				
Past performance		**0.1754**	**0.1700**	**0.1741**		**0.1869**		
		(2.39)	(2.31)	(2.28)		(3.24)		
Hedgers' hedging pressure		-0.0089		-0.0032				
		(-0.78)		(-0.23)				
Speculators' hedging pressure			0.0053	0.0046				
			(0.57)	(0.39)				
Average price					0.0000			
					(-0.01)			
Total volatility					1.0565			
					(1.49)			
Idiosyncratic volatility					**-1.8063**	-0.1660		
					(-1.98)	(-0.59)		
Kurtosis					0.0004			
					(0.46)			
$ open interest					0.0000			
					(-1.31)			
Commodity risk factors								
EW							0.0029	0.0027
							(1.48)	(1.34)
TS							-0.0008	-0.0002
							(-0.42)	(-0.11)
Mom							**0.0038**	**0.0039**
							(1.75)	(1.82)
HP							**0.0030**	**0.0033**
							(1.65)	(1.86)
Adjusted R-square	1.26%	9.72%	9.59%	10.07%	10.70%	9.01%	**26.79%**	25.82%

Table 6. Robustness of cross-sectional tests

This table tests the robustness of the cross-sectional results to the choices of ranking periods (R) (Panel A), asset pricing model (Panel B), definition of skewness (Panel C) and sub-samples (Panel D). The table reports in columns (1) and (2) the prices of skewness risk λ_{Sk} estimated from models (4) and (5) of Table 5, alongside t-statistics corrected using Newey and West (1987) or Shanken (1992), respectively. Bold fonts indicate significance at the 10% level or better. Unless specified otherwise, the sample covers the period January 1987 – November 2014.

	Commodity characteristics		Commodity risk factors		Traditional and/or commodity risk factors	
Panel A: Choice of ranking periods						
R = 6	**-0.0041**	(-1.73)	**-0.0088**	(-3.88)		
R = 12	**-0.0087**	(-3.95)	**-0.0086**	(-3.53)		
R = 36	**-0.0078**	(-2.03)	**-0.0083**	(-2.60)		
R = 60	-0.0047	(-1.23)	**-0.0075**	(-2.18)		
R = 96	**-0.0067**	(-1.78)	**-0.0086**	(-2.16)		
Average	-0.0064		-0.0084			
Panel B: Choice of asset pricing model						
Carhart (1997)					**-0.0107**	(-3.88)
Carhart (1997) + Barclays bond index					**-0.0113**	(-4.07)
Carhart (1997) + Barclays + EW + TS + Mom + HP					**-0.0097**	(-3.08)
Panel C: Definition of skewness						
Systematic skewness	0.0000	(-0.33)	0.0000	(0.12)		
Idiosyncratic skewness	**-0.0124**	(-3.97)	**-0.0093**	(-3.16)		
Expected idiosyncratic skewness	0.0108	(0.77)	**-0.0144**	(-2.41)		
Panel D: Sub-sample analysis						
Jan 1987-May 2001	**-0.0079**	(-2.85)	**-0.0121**	(-3.79)		
June 2001-Nov 2014	**-0.0099**	(-2.80)	-0.0052	(-1.41)		
Jan 1987-Dec 2005	**-0.0075**	(-2.85)	**-0.0098**	(-3.38)		
Jan 2006-Nov 2014	**-0.0111**	(-2.66)	-0.0064	(-1.35)		
Jan 1987-July 2007	**-0.0070**	(-2.82)	**-0.0094**	(-3.51)		
Aug 2007-Nov 2014	**-0.0135**	(-2.88)	-0.0066	(-1.18)		