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Abstract

This article studies the relation between the skewness of commodity futures returns and expected returns. A trading strategy that takes long positions in commodity futures with the most negative skew and shorts those with the most positive skew generates significant excess returns that remain after controlling for exposure to well-known risk factors. A tradeable skewness factor explains the cross-section of commodity futures returns beyond exposures to standard risk premia. The impact that skewness has on future returns is explained by investors' preferences for skewness under cumulative prospect theory preferences and selective hedging practices.

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1. Introduction

Recent research on equities has studied the relationship between skewness and expected returns. While theory predicts a negative relation between skewness and expected returns (Mitton and Vorkink, 2007; and Barberis and Huang, 2008), empirical results are mixed (*e.g.,* Kumar (2009), Bali *et al.* (2011), Amaya *et al.* (2015) find evidence in support of this negative relation, whereas Xiang *et al.* (2010), Cremers and Weinbaum (2010), and Rehman and Vilkov (2012) document a positive relation). Given these mixed results, a study that focuses on a different asset class can shed light on the relation between skewness and expected returns. In this paper, we fill this gap by focusing on commodity futures and examining whether the skewness of daily commodity futures returns tells us anything about expected returns on these futures. The answer to this question is of great importance to academics interested in developing commodity pricing models and more generally getting a better understanding about the role of skewness in the pricing of assets. It is also relevant to long-short market participants concerned with the design of practical investment solutions in commodity futures markets.

The literature on commodity futures pricing has established that a suitable benchmark should include a long-only commodity portfolio as well as long-short portfolios deemed to capture the phases of backwardation and contango (see Bakshi *et al.*, 2017 or Fernandez-Perez *et al*., 2017 for recent references). Acknowledging that backwardation (contango) signals a likely rise (fall) in futures prices, such long-short portfolios buy backwardated commodities described by lower standardized inventories (Fama and French, 1987; Symeonidis *et al.*, 2012; Gorton *et al*., 2013), downward sloping forward curves (Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006; Szymanowska *et al*., 2014; Koijen *et al.*, 2017), good past performance (Erb and Harvey, 2006; Miffre and Rallis, 2007; Asness *et al.*, 2013; Gorton *et al*., 2013), net short hedging and net long speculation (Bessembinder, 1992; Basu and Miffre, 2013; Dewally *et al.*, 2013); they also short contangoed commodities with opposite characteristics. Aside from these now-standard signals, the literature also documents significant spreading returns earned on portfolios sorted on liquidity, change in open interests, inflation beta, dollar beta, value or volatility (Hong and Yogo, 2012; Asness *et al.*, 2013; Szymanowska *et al.*, 2014). Expanding on this literature, we conduct time-series and cross-sectional tests to investigate the presence of a skewness-expected return association.

Using a time-series approach, we examine the performance of a long-short portfolio sorted on skewness where the latter is estimated over the past 12 months of daily futures returns. Taking fully-collateralized long positions in the 20% of commodities with the most negative skewness and short positions in those with the most positive skewness at each month-end generates an average excess return of 8.01% per annum that is statistically significant (*t*-statistic of 3.83). The average alpha of the long-short skewness-sorted portfolio stands at 6.21% per annum across pricing models and thus the excess return cannot be explained by standard pricing models documented in the literature. The time-series evidence is robust to transaction costs and liquidity considerations.

Cross-sectional tests show that the long-short skewness portfolio explains the pricing of commodity futures. The price of skewness is statistically significant and positive with an average of 5.04% per annum across models. In comparison to other factors, the skewness factor commands the most significant and largest premium. Including the skewness factor increases the average explanatory power of commodity pricing models marginally (from 31.77% to 35.26% or by 3.5%) but systematically.[1] These results corroborate the time-series evidence in showing that skewness matters to the pricing of commodity futures and that investors demand higher compensation for exposure to commodity futures with lower levels of skewness.

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[1] The rise in explanatory power obtained when moving from a given model to the same model augmented with a skewness factor, albeit small, is similar to that obtained in the equity literature (Chang *et al*., 2013).

Finding that skewness is a profitable signal in markets other than equities (*e.g.*, Chang *et al.*, 2013; Conrad *et al*., 2013; Amaya *et al.*, 2015) and equity derivatives (Bali and Murray, 2013; Boyer and Vorkink, 2014) indicates that the negative relation we observe between skewness and expected returns reflects a pervasive phenomenon that is unlikely to disappear after this and other articles are published. It further provides out-of-sample evidence on this growing literature (*e.g.*, Harvey and Siddique, 2000; Mitton and Vorkink, 2007; Adrian and Rosenberg, 2008; Barberis and Huang, 2008; Kumar, 2009; Boyer *et al.*, 2010; Bali *et al.*, 2011; Chang *et al.*, 2013; Conrad *et al.*, 2013; Boyer and Vorkink, 2014; Amaya *et al.*, 2015). Overall, our results lend support to the theories on skewness preferences (Mitton and Vorkink, 2007; Barberis and Huang, 2008). In these frameworks, skewness matters because of investors' preference for positive skewness (lottery-type payoffs), which causes positively skewed equities to become overpriced and earn lower expected returns than equities with negative skews. This overpricing is not arbitraged away either because of short-selling restrictions (Mitton and Vorkink, 2007) or because positive skewness has a valuable impact on the utility investors derive from their investments (Barberis and Huang, 2008).[2] Since commodity futures markets are not subject to short-sale constraints and are dominated by speculators and hedgers, with retail investors rarely participating, our findings are more in line with the cumulative prospect theory framework of Barberis and Huang (2008).

An additional mechanism through which skewness could affect commodity prices relates to selective hedging, or more specifically, to hedging under skewness preferences (Stulz, 1996; Gilbert *et al.*, 2006 and Lien and Wang, 2015). Selective hedging is a practice in which hedgers' view of future price movements influences their optimal hedge ratio. In this sense, hedgers with

[2] Barberis and Huang (2008) use the cumulative prospect theory framework of Tversky and Kahneman (1992) to show that overweighting the probabilities of the occurrence of tail events leads to a preference for positively skewed assets. As this preference for positive skewness is part of the utility functions of investors this is not arbitraged away by short positions.

preferences either described by cumulative prospect theory (Barberis and Huang, 2008) or influenced by skewness (Gilbert *et al.*, 2006) may not only want to minimize risk but also maximize skewness. Consistent with our empirical findings, these skewness preferences could increase net long hedging, and accordingly, overprice positively skewed commodities; and vice versa for negatively-skewed ones. Aligned with the selective hedging hypothesis, we show that commercial traders have a propensity to take relatively longer (shorter) hedges in positively (negatively) skewed commodities.

The rest of the article unfolds as follows. Section 2 presents the theoretical motivation of why skewness matters in commodity futures markets. Section 3 presents the commodity futures data and benchmarks. Section 4 examines the performance of the skewness trading strategy. Section 5 investigates the ability of a tradeable skewness factor to explain the cross-section of individual commodity returns. Finally Section 6 concludes.

2. Theoretical background

In this section, we discuss the theoretical background for why skewness can affect the expected returns of commodities. We focus specifically on the skewness preference literature, which argues that investor preferences affect demand for assets with certain distributional properties. In addition, we discuss the literature on selective hedging where hedgers' view of future price movements influences the exposure that is hedged.

There are two theoretical frameworks that motivate a negative relation between skewness and expected returns. The first framework by Mitton and Vorkink (2007) relies on the notion of two types of traders, one being the traditional mean-variance optimizer, while the other being a trader with an inherent preference for assets with positively skewed distributions (*i.e.*, lottery-like assets). This framework largely builds on a behavioral bias, where investors have an intrinsic preference for positive skewness (lottery-like equities) and hence, positive-skewness equities are overpriced and have lower expected returns than equities with negative skewness. The overpricing is not arbitraged away because of short-selling restrictions. Empirically, Kumar (2009) shows that those investors with preferences for lottery-type equities are typically retail investors.

The second framework (based on the work of Barberis and Huang, 2008) is different, in the sense that all investors have homogenous preferences, but have utility functions based on cumulative prospect theory preferences (Tversky and Kahneman, 1992). Under cumulative prospect theory preferences, investors have value functions that are concave over gains, but convex over losses (this makes investors risk averse over moderate gains, but risk seeking over moderate losses). In addition, investors overweigh the likelihood of events with low probabilities of occurring, and underweigh the likelihood of events with high probabilities of occurring. Barberis and Huang (2008) demonstrate that in an economy with skewed assets and short-selling constraints, positively skewed assets will become overpriced as investors overweigh the likelihood of extreme events occurring, and thus are willing to pay more for an asset with a higher chance of positive outcomes.

However, as Barberis and Huang (2008) point out, even in the case where investors *can* short-sell, under cumulative prospect theory preferences skewed assets will be mispriced. In the case of a positively skewed asset, investors would not be willing to short much of that asset, as it would expose them to the possibility of a large negative return, and since these investors overweigh the probability of these negative events occurring, they would find short position in positively skewed asset very unattractive unless they receive a premium for exposing themselves to this risk. Likewise, investors with cumulative prospect theory preferences would not prefer to hold negatively skewed assets, but actually prefer to short those assets (as that would essentially expose them to positive skewness). This suggests that even in the case where short-selling is allowed (as in commodity futures markets), we would observe that negatively skewed assets end up being underpriced, while positively skewed assets become overpriced. In our context, commodity investors may have preferences for positive skewed commodities or utility functions with cumulative prospect theory preferences that make them overprice (underprice) contracts with positive (negative) skewness.

A potential mechanism through which skewness preferences could affect commodity prices is *selective hedging* (see Stulz, 1996). Selective hedging is a practice in which the risk manager's view of future price movements influences the percentage of the exposure that is hedged. In this case, commercial traders do not fully hedge their positions; rather their hedging strategies incorporate a speculative component that depends on their anticipation of forthcoming price changes.

In this sense, if hedgers form preferences based on cumulative prospect theory (Barberis and Huang, 2008) or in general have skewness-based preferences (Gilbert *et al.*, 2006), they will favor an overall position (underlying plus hedge) that minimizes risk and at the same time maximizes skewness. For a short hedger (or producer), a positively skewed position in the commodity will result in a short futures position that falls short of her minimum variance hedge ratio (as taking a full short hedge would remove the positive skewness that the hedger seeks). Likewise, a long hedger (or consumer) in a positively skewed commodity will have a hedging demand that exceeds her minimum variance hedge ratio (as she then reverts the negative skewness she is exposed to in the underlying into a positive skewness). This implies that from a hedging demand side, we expect to see more net long hedging demand in positively skewed assets which makes them overpriced. Reversing the argument, we expect to see more net short hedging demand in negatively skewed assets which makes them underpriced.

Recent hedging literature highlights this potential mechanism. For instance, Gilbert *et al*. (2006) develop an optimal hedging model where hedgers care about mean, variance and skewness of the expected profit distribution (which include the positions in the spot and futures contracts) through a negative exponential utility function, and compare this with the optimal hedging positions under a mean-variance utility framework. Under the assumption that the futures price is a biased estimate of the expected future spot price, they demonstrate that positive skewness reduces the short hedging, and likewise, a negative skewness of the spot prices increases the short hedging. Lien and Wang (2015) show that under the assumption of a skewed Student *t*-distribution for the spot price and negative exponential utility for the producer, the producers will hedge more (less) when negative (positive) skewness prevails compared with a mean-variance hedger. In both papers, skewness of the underlying has an effect on the hedgers' hedging positions and thus the demand for futures.

3. Data and Pricing Models

3.1. Description of Commodity Futures Data

Our main data for the analysis are daily settlement prices from *Datastream* on front-end and second-nearest futures contracts for 27 commodities from distinct sectors: agriculture (cocoa, coffee C, corn, cotton n°2, frozen concentrated orange juice, oats, rough rice, soybean meal, soybean oil, soybeans, sugar n°11, wheat), energy (electricity, gasoline, heating oil n°2, light sweet crude oil, natural gas), livestock (feeder cattle, frozen pork bellies, lean hogs, live cattle), metal (copper, gold, palladium, platinum, silver), and random length lumber. Returns are changes in log prices of the front-end contract up to one month before maturity; we then roll to the second-nearest contract. The sample period is January 1987 to November 2014.

We compute the Pearson's *moment coefficient of skewness* of each commodity at month-end t using the daily return history in the preceding 12-month window

$$\widehat{Sk}_{i,t} = \left[\frac{1}{D}\sum_{d=1}^{D}\left(r_{i,d,t} - \hat{\mu}_{i,t}\right)^3\right] / \hat{\sigma}_{i,t}{}^3 \tag{1}$$

where $r_{i,d,t}, d = 1, \ldots, D$ are the daily returns of the *i*th commodity, D is the number of daily observations within the [*t*-11, *t*] window, and the parameters $\hat{\mu}_{i,t} = \frac{1}{D}\sum_{d=1}^{D} r_{i,d,t}$ and $\hat{\sigma}_{i,t}{}^2$ $=\left[\frac{1}{D-1}\sum_{d=1}^{D}\left(r_{i,d,t} - \hat{\mu}_{i,t}\right)^2\right]$ are the mean and variance estimates of the daily return distribution, respectively. The higher the absolute value of the skewness measure, the more asymmetric the distribution.

Figure 1 plots for illustrative commodities from each sector (corn, crude oil, gold and feeder cattle) the evolution of $\widehat{Sk}_{i,t}$ alongside the 95% confidence bands; the legend of the graph summarizes for each commodity *i* the percentage of sample months *t*=1,…,T with significant $\widehat{Sk}_{i,t} < 0$ and $\widehat{Sk}_{i,t} > 0$. Table I summarizes the distribution of skewness of individual commodity futures returns by providing the mean, 25th quantile, median (50th quantile), 75th quantile and standard deviation of $\{\widehat{Sk}_{i,t}\}_{t=1}^{T}$ where *T* are the sample months.

[Insert Figure 1 and Table I around here]

The graphs in Figure 1, along with the standard deviation and 25th versus 75th percentile statistics in Table I, show that, despite the overlapping nature of the 12-month observation windows of daily data used to compute $\{\widehat{Sk}_{i,t}\}_{t=1}^{T}$ (at a monthly rolling frequency), the skewness of commodity futures returns varies considerably over time, changing sign too. The percentage of months when the skewness coefficient attains a positive (negative) value ranges between 20% and 71% (29% and 80%) across the 27 commodities and averages 43% (57%).[3]

3.2. Commodity Risk Factors

To properly address the question of whether skewness matters, we place our forthcoming time-series and cross-sectional analyses in the context of a baseline and augmented commodity

[3] Commodity futures prices are observationally equivalent to non-stationary process and therefore the moments may not be constant. Effectively, this means that the skewness of the price distribution is potentially problematic as it may not converge to any meaningful value as D increases.

pricing models as outlined next in Sections 3.2.1 and 3.2.2, respectively. Section 3.2.3 discusses various summary statistics for the set of commodity risk factors employed.

3.2.1. *Baseline Commodity Pricing Model*

Bakshi *et al.* (2017) construct three systematic risk factors as the excess returns of an *equally-weighted long-only* portfolio of all commodity futures (*EW* factor, hereafter) that they refer to as the average commodity factor, a *term structure* portfolio (*TS*) and a *momentum* portfolio (*Mom*). Basu and Miffre (2013) advocate a *hedging pressure* (*HP*) factor. Whereas the *EW* factor is meant to capture overall commodity market risk, the *TS*, *Mom* and *HP* factors proxy for the risks associated with the backwardation/contango cycle of commodity futures markets. The beta-expected return representation of the baseline four-factor model can be written as

$$E_t\left(r_{i,t+1}\right) = \lambda_{EW}\beta_{iEW,t} + \lambda_{TS}\beta_{iTS,t} + \lambda_{Mom}\beta_{iMom,,t} + \lambda_{HP}\beta_{iHP,t} = \boldsymbol{\lambda_F \beta_{iF,t}} \tag{2}$$

where i is a commodity futures, $\boldsymbol{F_t} \equiv (EW_t, TS_t, Mom_t, HP_t)'$ are the risk factors, $\boldsymbol{\lambda_F} \equiv (\lambda_{EW}, \lambda_{HP}, \lambda_{Mom}, \lambda_{HP})'$ collects the vector of factor risk premia, which is common to all commodities, and $\boldsymbol{\beta_{iF,t}} \equiv (\beta_{iEW,t}, \beta_{iTS,t}, \beta_{iMom,t}, \beta_{iHP,t})'$ are the commodity-specific factor betas or loadings which represent scaled conditional covariances.

The *EW* portfolio is a long-only, equally-weighted and monthly-rebalanced portfolio of all commodity futures. The factors, referred to as *TS*, *Mom* and *HP*, are the excess returns of long-short fully-collateralized portfolios of commodity futures that long (short) the most backwardated (contangoed) quintile. The *TS* and *HP* risk factors are directly motivated by the theories of storage and hedging pressure, respectively. The *Mom* factor can also be motivated, albeit indirectly, by the theory of storage. For most commodities, the replenishing of scarce inventories through production in backwardated markets or the depletion of abundant inventories through consumption in contangoed markets is a lengthy process during which price continuation will occur. To put it differently, scarce (backwardated) commodities are likely to be momentum winners and abundant (contangoed) commodities are likely to be momentum losers (Miffre and Rallis, 2007; Gorton *et al.*, 2013).

To construct the *TS*, *Mom* and *HP* risk factors, we average the following signals over a prior 12-month ranking period and hold the long-short portfolios on a fully-collateralized basis for a month. The signal employed in the construction of the long-short *TS* portfolio is the *roll yield* measured for each commodity as the daily difference in the logarithmic prices of the front-end and second-nearest contracts; the portfolio buys (and simultaneously sells) the quintile with highest (lowest) average roll-yield over the previous 12 months. The long-short *Mom* portfolio is based on *past performance* over the past 12 months; the portfolio buys (sells) the quintile with highest (lowest) average return over the previous 12 months. Finally, the pertinent signal for the construction of the long-short *HP* portfolio is the hedgers' and speculators' *hedging pressure* measured for each commodity as $HP_H \equiv \frac{Long_H}{Long_H + Short_H}$ and $HP_S \equiv \frac{Long_S}{Long_S + Short_S}$, respectively; where $Long_H$ ($Long_S$) and $Short_H$ ($Short_S$) denote the open interests of long and short hedgers (speculators), respectively;[4] the long-short *HP* portfolio buys (sells) the quintile with the lowest (highest) HP_H *and* highest (lowest) HP_S. The time span of our sample together with the choice of ranking period imply that we obtain monthly observations for the risk factors from January 1987 to November 2014. The choice of a "long" ranking period of 12 months is motivated by the slow evolution of the backwardation/contango cycle as suggested by the theory of storage and hedging pressure hypothesis (*e.g.*, Gorton *et al.*, 2013).

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[4] The Commodity Futures Trading Commission (CFTC) classifies traders based on the size of their positions as large (reportable) or small (non-reportable). The reportable category accounts for 76% of long open interest and 80% of short open interest on average across commodities in our sample period. Non-reportable traders are not required to specify the motives of their positions but reportable traders have to inform the CFTC as to whether they are commercial (hedgers) or non-commercial (speculators) participants. These declarations are checked, summarized in the Aggregated Commitment of Traders Report and published on the CFTC website going back to January 1986.

3.2.2. *Augmented Commodity Pricing Models*

We augment the baseline commodity pricing model (featuring the EW_t, TS_t, Mom_t and HP_t factors) with a set of factors that is deemed to explain the pricing of commodity futures (Hong and Yogo, 2012; Asness *et al.*, 2013; Szymanowska *et al.*, 2014). This set of additional systematic factors that may price commodity futures includes *i*) a *liquidity* risk factor based on (as sorting signal) the daily Amihud *et al.*'s (1997) dollar volume to absolute return ratio averaged over the two most recent months, *ii*) an *open interest* (ΔOI) factor deemed to capture future price inflation and based on the changes in the open interest of individual commodities at the time of portfolio formation, *iii*) an *inflation* factor constructed according to the slope coefficient β of prior 60-month regressions of monthly commodity futures returns on unexpected inflation measured as the change in one-month U.S. CPI inflation rate, *iv*) a *currency* risk factor constructed according to the slope coefficient β of prior 60-month regressions of monthly commodity futures returns on the changes in the U.S. dollar versus a basket of foreign currencies, *iv*) a *value* factor that picks up long-run mean reversion by sorting commodities on the log of the average daily front-end futures prices from 4.5 to 5.5 years ago divided by the log of the front-end futures price at time *t*, and *vi*) a *volatility* factor, net of the momentum effect, constructed as the *coefficient of variation* (CV) of daily futures returns over the prior 36 months. The literature has shown that contracts with low liquidity, rising OI, high inflation betas, low dollar betas, high value and high CV outperform those at the other extreme (Erb and Harvey, 2006; Hong and Yogo, 2012; Asness *et al.*, 2013; Szymanowska *et al.*, 2014).

Similar to our definition of *TS*, *Mom* and *HP* factors, these additional systematic factors are defined as the excess returns of long-short quintiles with the long and short positions held for one month on a fully-collateralized basis. Appendix A provides further details.

3.2.3. *Descriptive Statistics for the Risk Factors*

Table II presents descriptive statistics for the risk factors employed in the paper. Beginning with the commodity risk factors, the results confirm the importance of capturing the phases of backwardation and contango when modelling the risk premium of commodity futures. Over the period January 1987 to November 2014, the *TS*, *Mom* and *HP* portfolios outperform all other commodity portfolios. For example, the mean excess returns of the *TS*, *Mom* and *HP*-sorted portfolios range from 4.63% to 8.95% *p.a.*, all of which are significant at the 5% level or better. In sharp contrast, the other commodity portfolios earn at best 3.52% *p.a.* and none of the mean excess returns is significant at the 10% level. The risk-adjusted performance metrics reported in Table II, Sharpe and Omega ratios, unanimously confirm the outperformance of the *TS*, *Mom* and *HP* portfolios among all commodity portfolios.[5] Panel C of Table II reports summary statistics for the S&P-GSCI, the well-known equity (market portfolio, SMB, HML and UMD) risk factors and bond (Barclays) risk factor, which we eventually employ in various robustness checks. Appendix B shows that the pairwise correlations amongst the other long-short factors are small. This motivates their joint inclusion into the various pricing models employed.

[Insert Table II around here]

4. Time-Series Portfolio Setting

4.1. Characteristics of Skewness-Sorted Portfolios

We conduct *time-series* tests of the relationship between commodity futures skewness and expected returns using a long-short portfolio approach. To do so, at the end of each month, *t*,

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[5] Additional summary statistics computed separately for the *long* and *short* portfolios confirm the stylized fact that backwardated (contangoed) contracts appreciate (depreciate) in value. For concreteness, the long *TS*, *Mom* and *HP* portfolios earn positive mean excess returns of 4.24% (*t*-statistic of 1.05), 7.41% (*t*-statistic of 1.61) and 2.29% (*t*-statistic of 0.58) *p.a.*, respectively; while the short *TS*, *Mom* and *HP* portfolios earn negative mean excess returns of -5.03% (*t*-statistic of -1.36), -10.49% (*t*-statistic of -2.54) and -9.28% (*t*-statistic of -2.53) *p.a.*, respectively. Since the long-short portfolios are fully collateralized their return is half that of the longs minus half that of the shorts.

we estimate the Pearson's *moment coefficient of skewness* ($\widehat{Sk}_{i,t}$) of the daily return distribution of commodity $i = 1, \dots, N$ using the data available within the most recent month t-11 to month t window.[6] Then at each month-end t, we rank the $i = 1,\dots,N$ commodities in the cross-section ($N = 27$) according to their $\widehat{Sk}_{i,t}$ values and group them into five portfolios or quintiles; quintile Q1 contains the 20% of commodities with the lowest $\widehat{Sk}_{i,t}$, and so forth, up to quintile Q5 that contains the 20% of commodities with the highest $\widehat{Sk}_{i,t}$.

We start by examining some of the properties of the skewness portfolios by looking at the characteristics of the different quintiles. Table III summarizes the results with Panel A focusing on the pre-ranking skewness of the quintiles. Since this is precisely the signal used to group the commodities into quintiles, it is not surprising to see that $\overline{Sk}$ is negative for Q1 at -0.73 and positive for Q5 at 0.54, and the differential $\overline{Sk}_{Q1} - \overline{Sk}_{Q5}$ is strongly significant at the 1% level as suggested by the Newey-West (1987) *h.a.c.* robust t-statistic reported in the last column of the table.

[Insert Table III around here]

Then we turn attention to four signals – roll-yield, past performance, hedgers' hedging pressure and speculators' hedging pressure – that are well-known to capture the backwardation and contango cycle. The signals are measured at each month-end t over the same 12-month rolling observation windows as the $\widehat{Sk}_{i,t}$ signal, and the statistics reported are again averages. The main conclusion that can be gleaned from Panel B of Table III is that the constituents of Q1 present backwardated characteristics such as higher roll-yield, better performance, higher speculators' hedging pressure and lower hedgers' hedging pressure. Vice versa, the constituents

[6] For expositional clarity, throughout the paper our skewness signal is obtained employing a ranking period R=12 months and a holding period H=1 month. Nevertheless, in additional unreported results, we considered different ranking and holding periods R={6, 36, 60, 96} and H={3, 6, 12}. The main empirical findings remain unchallenged. Detailed results are available upon request.

of Q5 present contangoed characteristics such as lower roll-yield, worst past performance, lower speculators' hedging pressure and higher hedgers' hedging pressure. The difference in roll-yield between Q1 and Q5 is highly significant at the 1% level; likewise for hedgers' hedging pressure and speculators' hedging pressure. For these three signals, there are clear monotonic patterns across quintiles; *e.g.*, the speculators' hedging pressure decreases without exception from 0.6570 for the most negative-skew commodities (Q1) to 0.5848 for the most positive-skew commodities (Q5). The difference in past performance (excess return *p.a.*) across Q1 and Q5 is also significant albeit only at the 10% level. Hence, in assessing whether skewness contains information about expected returns, we need to control for these traditional risk factors.

4.2. Summary Statistics for the Performance of the Skewness-Sorted Portfolios

Figure 2 illustrates the cumulative logarithmic returns ($cr_t = \sum_{j=1}^{t} r_j \, , t = 1, \dots, T$) of each skewness-sorted quintile. Monotonically, the end-of-period cumulative returns of the skewness quintiles are inversely related to the degree of skewness; that is, $cr_{Q1,T} > cr_{Q2,T} > \cdots > cr_{Q5,T}$. For concreteness, the end-of-period cumulative return of the most negatively-skewed portfolio Q1 amounts to a gain of about 150% (or 5.12% *p.a.*) whereas that of the most positively-skewed portfolio Q5 amounts to a loss of about 300% (or 10.89% *p.a.*).

[Insert Figure 2 around here]

A potential concern that one could raise is that the returns of the different quintile portfolios could be driven by a few commodities that persistently end up in the high or low skewness portfolios. To address this concern, Figure 3 shows the frequency of portfolio formation months $t = 1,\dots,T$ that each commodity enters the long (Q1) and short (Q5) portfolio per sector. None of the frequencies comes near 100% (most below 50%) which confirms that none of the commodities is perpetually part of the Q1 or Q5 portfolios; in other words, different commodities enter the extreme (most positive or negative) skewness portfolios over time.

[Insert Figure 3 around here]

The observation that commodities in Q5 outperform those in Q1 as observed in Figure 2 motivates us to examine a commodity skewness trading strategy: a monthly-rebalanced "low-minus-high skewness" portfolio (or long-short skewness portfolio, hereafter) that buys Q1 and shorts Q5. Table IV summarizes the 1-month returns accrued by the individual long-only (quintiles) portfolios and by the long-short skewness portfolio. All portfolios are fully-collateralized and returns are in excess of the risk-free rate.

[Insert Table IV around here]

Panel A of Table IV shows that mean excess returns decrease monotonically from the most negatively (Q1) to the most positively skewed portfolio (Q5). The mean excess return of Q1 is positive at 5.12% a year (Newey-West *t*-statistic of 1.42), and that of Q5 is negative at -10.89% a year (Newey-West *t*-statistic of -3.35). With regards to risk, the standard deviation of Q1 is larger than that of Q5. In terms of risk-adjusted performance, and as consistently suggested by the Sharpe, Sortino and Omega ratios, portfolio Q1 outperforms portfolio Q2, portfolio Q2 outperforms portfolio Q3, and so forth in a monotonic fashion. As the penultimate column of Table IV reveals, taking simultaneous fully-collateralized long positions in the most negative-skew commodities (Q1) and short positions in the most positive-skew commodities (Q5) at each month-end *t* of the sample period yields a mean excess return of 8.01% a year (Newey-West *t*-statistic of 3.83), a Sharpe ratio of 0.7848 and an Omega ratio of 1.8136. We should note that these performance measures are better than those of the long-short *TS*, *Mom* and *HP* portfolios typically used as risk factors in the literature on commodity futures pricing (*c.f.*, Table II).[7]

[7] Inspired by Harvey and Siddique (2000) and other studies in the equity market literature, we sort commodities into quintiles based on their co-skewness with a market proxy M made of 90% of stocks and 10% of commodities (the co-skewness signal is the slope coefficient on the M^2 returns in a regression of daily commodity futures returns onto M and M^2 returns). The long-short systematic co-skewness portfolio yields a Sharpe ratio of 0.1132, which is much lower than that reported in Table IV (0.7848). The skewness signal, Equation (1), therefore conveys more information about expected commodity futures returns than co-skewness.

The performance of the long-short portfolios appears to be more driven by the relatively large negative return and low volatility of the shorts (Q5) than by the lesser positive return and higher volatility of the longs (Q1). The performance of the fully-collateralized long-short skewness portfolio is quite alluring both relatively-speaking (*i.e.*, compared to each of the individual, long-only Q1 to Q5 portfolios) and absolutely due to its high 8.01% excess return *p.a.*, low risk (*e.g.*, low volatility, 99% VaR, and maximum drawdown), and high Sharpe, Sortino and Omega ratios. These results show that the skew of the distribution of daily commodity futures returns conveys information about subsequent returns; namely, there is a significantly negative relation between skewness and expected returns.[8]

Panel A of Table IV also reports the average post-ranking skewness of the quintile returns, where the latter is measured by first calculating the skewness of each constituent using daily returns in the holding period and then averaging these skewness measures for a given quintile across constituents and over time. Relative to the pre-ranking skewness reported in Panel A of Table III, the post-ranking skewness measures do not rise monotonically from Q1 to Q5 and show little variation across quintiles (range of [-0.10, -0.01] for the post-ranking skewness versus [-0.73, 0.54] for the pre-ranking skewness). Panel A of Table IV also reports the skewness of portfolio returns per quintile and again we do not observe any monotonic increase in skewness going from Q1 to Q5. These results are in line with the observations in Figures 1 and 3 and show that commodity skewness is time-varying, which leads to different commodities making up the extreme quintiles over time.

Overall, Table IV demonstrates that positively (negatively) skewed commodities underperform (outperform), which is in line with the skewness preference theories discussed in

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[8] We filter out from Q1 (Q5) those commodities with non-negative (non-positive) $\widehat{Sk}_{i,t}$. The performance measures for the resulting long-short portfolio are nearly identical to those reported in Table IV, *e.g.* a mean excess return of 7.93%, Sharpe ratio of 0.78 and Omega ratio of 1.80.

Section 2. These results are also consistent with the notion that commercial participants engage in selective hedging and, for example, take longer hedging positions in positively skewed commodities to reflect upon their preference for positive skewness. As a result these positively-skewed commodities become overpriced and subsequently underperform.

4.3. Alpha and Factor Decomposition

Seeking to ascertain whether the profitability of the skewness portfolios is merely a compensation for exposure to commodity risk factors, we measure the alpha of the skewness trading strategy relative to the baseline four-factor commodity pricing model

$$r_{P,t} = \alpha_P + \beta_{P,EW} EW_t + \beta_{P,TS} TS_t + \beta_{P,Mom} Mom_t + \beta_{P,HP} HP_t + \upsilon_{P,t}, \ t = 1, \dots, T \qquad (3)$$

where $r_{P,t}$ denotes the month *t* return of either the long-short skewness portfolio or the individual long-only Q1 to Q5 portfolios. The parameter vector $(\alpha_P, \beta_{P,EW}, \dots, \beta_{P,HP})'$ is estimated by Ordinary Least Squares (OLS) and inferences are based on Newey-West robust *t*-statistics. Table IV, Panel B, presents the results. Q1 (Q5) has positive (negative) loadings on the *TS* and *HP* risk factors, albeit they are only significant for the Q1 regression. The sign of these loadings suggests that the negative-skew quintile Q1 tends to display more backwardated characteristics than the positive-skew quintile Q5. Accordingly, the *TS* and *HP* risk loadings in the long-short skewness portfolio are positive but only the beta of the *TS* risk factor is significant as suggested by a robust *t*-statistic of 2.74.

The most important finding is that the baseline four-factor model cannot fully explain the outperformance of Q1 and the underperformance of Q5. The alphas of the five skewness quintiles decrease monotonically from 4.28% a year (*t*-statistic of 1.79) for Q1 to -8.89% a year (*t*-statistic of -3.96) for Q5. The risk-adjusted excess return of the fully-collateralized long-short skewness portfolio is a non-negligible 6.58% a year (*t*-statistic of 3.58). This inference is not challenged when we employ bootstrap *p*-values (reported in curly brackets) to account for the possibility of non-normality in the alpha distribution.[9]

The alpha of 6.58% *p.a.* accrued by the long-short skewness portfolio is not much smaller than its mean excess return of 8.01% *p.a.* (Panel A of Table IV). This suggests that the outperformance of the long-short skewness portfolio is not merely compensation for exposure to the backwardation and contango risk factors. This result is confirmed by the low adjusted-R^2 of the four-factor benchmark fitted to the long-short skewness portfolio returns (5.66%) and by the low correlations between the skewness excess returns and the *TS*, *Mom* and *HP* factors (in the last row of Appendix B).

4.4. Robustness Tests

We now assess the robustness of the performance of the long-short skewness portfolio to various considerations. We begin by addressing the time-dependence issue by carrying out conditional tests in the same spirit of Lewellen and Nagel (2006). To visualize the time-variation in the alpha, we deploy the long-short portfolio strategy based on the $\widehat{Sk}_{i,t}$ signal over seven-year subsamples that are rolled forward monthly. Figure 4 plots the alphas together with 95% confidence bands based on Newey-West standard errors. The magnitude of the alpha changes over time as one would expect but the significance of the alpha is quite pervasive. Consistent with the preceding unconditional results, the average conditional alpha is positive and significant at 8.53% a year (Newey-West *t*-statistic of 21.74).

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[9] We construct *B*=10,000 sequences of bootstrap residuals, $\{\hat{v}_t^i\}_{t=1}^T$, $i = 1, 2, \dots, B$, by concatenating random blocks (length *M*) drawn from the residuals of regression (3). Using these artificial residuals and the original regression parameter estimates we simulate *B* time-series of portfolio returns under the null hypothesis ($\alpha = 0$) and then re-estimate regression (3) with each of them. The bootstrap *p*-value is $Min\{P(\hat{\alpha}^i > \hat{\alpha}), 1 - P(\hat{\alpha}^i > \hat{\alpha})\}$ where $P = \sum I(\hat{\alpha}^i > \hat{\alpha})/B$ with $\hat{\alpha}$ and $\{\hat{\alpha}^i\}_{i=1}^B$ the original estimate and the estimates of alpha over bootstrap replications, respectively. We empirically verify that *M*=10 suffices to obtain *B* sequences of bootstrap residuals with similar autocorrelation properties (average 1st order autocorrelation 0.25) as the sequence of original residuals (1st order autocorrelation 0.28).

[Insert Figure 4 around here]

Table V shows the annualized alphas of long-short skewness-sorted portfolios for various additional tests, their corresponding Newey-West significance t-statistics in parentheses and bootstrap p-values in curly brackets. We begin by measuring the commodity skewness, Equation (1), at the end of each month t using filtered-returns instead of observed returns as until now. These filtered returns are residuals of regressions of the daily commodity futures excess returns spanned in [t-11, t] windows on an intercept and *i*) the baseline four systematic risk factors, *ii*) business cycle indicators[10] and/or *iii*) calendar-month dummies (deemed to capture seasonality in supply and demand). We then proceed as before and form long-short portfolios by sorting commodities according to the thus-obtained skewness $\widehat{Sk}_{i,t}^{*}$. The results in Panel A of Table V indicate that the alphas of the long-short $Sk_{i,t}^{*}$-sorted portfolios remain economically sizeable and statistically significant. Altogether, this first batch of robustness checks suggest that the negative skewness-expected return relation uncovered is not driven by exposure to backwardation and contango, the ups and downs of the business cycle and the phases of production and consumption.

[Insert Table V around here]

In Panel B, we measure the alpha of the long-short skewness strategy with reference to *i*) a four-factor model that employs the long-only S&P-GSCI returns (instead of the *EW* portfolio returns) as proxy for the overall commodity market portfolio, and *ii*) augmented versions of the baseline pricing model that includes additional systematic risk factors. We add the additional factors described in Section 3.2.2, in turn, and also estimate "kitchen sink" pricing models that

[10] Following the literature, the business cycle indicators are the default spread (yield differential between BAA and AAA bonds), TED spread (3-month LIBOR minus 3-month T-bill rate), term spread (10-year T-bond minus 3-month T-bill yield), daily change in VXO index and, given our commodity focus, the change in the Baltic Dry index (Bakshi *et al.*, 2012). Interest rates and VXO data are obtained from the FED and CBOE websites, respectively, and Baltic Dry Index from Bloomberg.

features all systematic factors. The sign and significance of the resulting alphas are not challenged by these benchmark re-specifications. For completeness, the bottom part of Panel B reports the alpha of the long-short skewness portfolio relative to traditional pricing models employed in the equity market and bond market literatures which remain sizable.

Our next batch of robustness tests, reported in Panel C of Table V, addresses liquidity and transaction costs issues. To address concerns relating to illiquidity, we systematically exclude at each formation point the 20% of commodities with the lowest liquidity according to the Amihud *et al.* (1997) measure and reconstruct the long-short skewness portfolios on the remaining cross-section. The alpha of the resulting long-short portfolio relative to the baseline four-factor model remains positive and significant. To address matters pertaining to transaction costs, we calculate the alpha of the long-short skewness portfolio after subtracting from traded returns twice the transaction cost estimate of Locke and Venkatesh (1997) or twice 0.033%. We also calculate the break-even transaction cost (or cost per trade that would be needed to wipe out all excess returns) of the skewness strategy and find it equal to 0.933%. Both of these tests show that transaction costs have a negligible effect on skewness profits.

Taken altogether, the robustness tests presented in this section suggest that the effect of skewness on expected returns is robust to how skewness is measured, alternative asset pricing model and illiquidity and transaction costs.

5. Cross-sectional Asset Pricing Tests

The time-series evidence presented in the previous section motivates us to ask whether a tradeable skewness factor can explain the cross-section of commodity futures over and above well-known commodity risk factors.

5.1. Tradeable Skewness Factor

In this section we test whether the tradeable skewness factor calculated as the difference in returns between Q1 and Q5 explains the cross-section of excess returns for individual commodity futures. For expositional clarity, we use the notation S_t for the tradeable skewness factor to distinguish it from the commodity-specific skewness signal denoted $Sk_{i,t}$. Let the baseline representation of the pricing model be formalized as in Equation (2). We re-specify it by adding the tradeable skewness factor as follows

$$E_t(r_{i,t+1}) = \lambda_S \beta_{i,t}^S + \boldsymbol{\lambda_F} \boldsymbol{\beta}_{i,t}^F \tag{4}$$

and estimate both models (baseline and augmented) by OLS using the Fama and MacBeth (1973) approach. Accordingly, we estimate pass-one time-series regressions month-by-month (daily data) to obtain the commodity sensitivities or monthly betas to the risk factors

$$r_{i,t,d} = \alpha_{i,t} + \beta_{i,t}^S S_{i,t,d} + \boldsymbol{\beta}_{i,t}^{F'} \boldsymbol{F}_{t,d} + v_{i,t,d}, d = 1, \dots, D \tag{5}$$

with *D* the number of days in month *t*. Then we estimate the pass-two cross-sectional regression

$$r_{i,t} = \lambda_{0,t} + \lambda_{S,t} \hat{\beta}_{i,t}^S + \boldsymbol{\lambda}_{F,t} \widehat{\boldsymbol{\beta}}_{i,t}^F + e_{i,t}, i = 1, \dots, N \tag{6}$$

on each month (t=1,…,T) of the sample period. We report the average *lambdas* of the pass-two cross-sectional regression (6) which includes the skewness factor, and of the counterpart regression without the skewness factor, $r_{i,t} = \lambda_{0,t} + \boldsymbol{\lambda}_{F,t} \widehat{\boldsymbol{\beta}}_{i,t}^F + e_{i,t}$. We also compare the explanatory power of both pass-two regressions and test the statistical significance of the price of skewness, H_0: $\bar{\lambda}_S = 0$, using Shanken's (1992) *t*-statistics. We repeat these cross-sectional pricing tests by augmenting Equation (2) with the factors discussed in Section 3.2.2.

Table VI presents the pass-two cross-sectional estimation results. Model A focuses on the baseline four-factor model, Models B to H consider additional systematic risk. The most striking and novel result of Table VI is the pervasive rejection of the hypothesis that the tradable skewness factor is not priced at the 5% significance level or better. The average price of skewness priced factor λ_{Sk} equals 0.0042 a month or 5.02% *p.a*. Thus, investors demand a higher compensation or premium for exposure to commodity futures with lower levels of skewness. Albeit small, we notice a systematic increase in explanatory power when switching from a given pricing model to an extended version thereof that includes the tradeable skewness factor. On average, explanatory power in Table VI rises from 31.77% to 35.26% or by 3.5%. This increase in adjusted R-square is similar to that obtained in equity markets (Chang *et al*., 2013).

[Insert Table VI around here]

The conclusion that skewness is priced cross-sectionally holds within the baseline pricing model that captures the phases of backwardation and contango (Model A) and shows that skewness is not merely another proxy for the phases of backwardation and contango. The *Mom* and *HP* risk factors relating to the fundamentals of backwardation and contango are found to pervasively price the cross-section of commodity returns. On average λ_{Mom} and λ_{HP} equal 0.0040 and 0.0035 per month which amount to annualized risk premia of 4.76% and 4.17%, respectively. This result, alongside the insignificance of the price of risk associated with the long-only *EW* risk factor, stresses the wisdom that the risk premia of commodity futures markets can only be captured in a long-short portfolio setting. These results align well with the summary statistics reported in Table II and with the literature (*e.g.*, Basu and Miffre, 2013). The "kitchen sink" model (Model H) explains close to 50% of the cross-sectional variation in the excess returns of individual commodities. Altogether four risk factors are found to have significant pricing power at the 10% level or better; these are based on skewness, momentum, hedging pressure, and value. In comparison to other factors, the skewness factor is found to command the most significant and largest premium.[11]

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[11] We also consider the 29 commodity portfolios formed by sorting the commodities into quintiles using skewness, roll-yield, past performance, hedgers' hedging pressure or speculators' hedging pressure signals, and 4 additional sector portfolios – agriculture, energy, livestock and metal – that monthly-rebalance and equally-weight constituent commodities. The skewness factor is significantly positively priced with an average price of 0.0063 a month or 7.52% *p.a*..

5.2. Robustness Checks

We first deploy the Fama-McBeth two-step regressions conditionally using seven-year rolling windows. The focus is on Equation (6), referred to as Model A in Table VI, and the parameter of interest is the price of the skewness factor. Figure 5 plots the $\hat{\lambda}_{S,t}$ together with 95% confidence bands based on the Shanken (1992) standard errors. The price of skewness $\hat{\lambda}_{S,t}$ is not constant over time, as one would expect, but it is generally positive.

[Insert Figure 5 around here]

Table VII shows additional analyses conducted to assess the robustness of the previous cross-sectional results. For this purpose, first we alter the signal used to construct the tradeable skewness factor in Panel A constraining the analysis to the baseline pricing model (Model A of Table VI). Second, we use the same skewness signal, Equation (1), but alter the pricing model in Panel B. The table reports the average cross-sectional price of skewness factor $\bar{\lambda}_S$ and the significance Shanken's (1992) robust *t*-statistic. The last two columns in each panel are the explanatory power of the pricing model and its simpler version without the tradable skewness factor.

[Insert Table VII around here]

As shown in Panel A, when the tradeable skewness factor is constructed using the daily commodity futures returns stripped of *i*) the systematic EW, Mom, TS and HP risks; *ii*) business cycle; or *iii*) monthly seasonality, reassuringly, the significantly positive price of skewness factor is not challenged. These cross-sectional results reinforce the evidence from the time-series portfolio analysis in Section 4 leading us to more firmly assert that the skewness signal is not simply a manifestation of (and thus it conveys information beyond) the phases of backwardation and contango. The information content of skewness is not an artifact either of the ups-and-downs of the business cycle nor of seasonality in supply and demand.

Panel B of Table VII shows that replacing the *EW* portfolio with the S&P-GSCI portfolio as alternative proxy for the average commodity factor or using traditional pricing models emanating from the equity and bond literature does not qualitatively alter the findings on the skewness factor pricing. Overall, Table VII confirms the previous results (c.f., Table VI) that the tradable skewness factor is significantly positively priced at 0.0044 or 5.23% *p.a.* on average. Adding the skewness factor to a given pricing model increases explanatory power by 4.05% on average.

Finally, we run additional cross-sectional regressions that include the original characteristics instead of the factor loadings in the second step of the Fama-McBeth regressions. Taking, for example, the baseline model, this amounts to replacing the slope vector $\boldsymbol{\beta}_{i,t}^{F}$ in (4) by lagged characteristics such as roll-yield, futures returns, hedgers' and speculators' hedging pressure as averaged over the previous 12 months. Table VII, Panel C reports $\bar{\lambda}_S$, the average slope coefficient obtained in the second stage on the skewness signal, its associated Newey-West *t*-statistic, as well as the adjusted-R^2 of models that include and exclude the skewness signal. Irrespective of the specification considered, the skewness signal is negatively priced corroborating once again the presence of a negative relationship between skewness and expected returns. Its inclusion in the pricing equation raises explanatory power systematically throughout models but only slightly (by an average of 1.41%).

6. Conclusions

This article studies the relationship between past skewness and expected returns in commodity futures markets, providing an important out-of-sample test on this relation observed in equities. Using a time-series portfolio analysis and cross-sectional pricing tests, we demonstrate that the skewness of commodity futures returns contains information about subsequent returns and, in particular, the direction suggests a negative skewness-expected returns relation. A tradeable skewness factor that buys the most negatively-skewed commodities and shorts the most positively-skewed commodities commands a premium that is economically and statistically larger than the risk premiums previously identified. The long-short skewness portfolio earns a sizeable alpha relative to a battery of benchmarks deemed to capture commodity risk factors. Through cross-sectional pricing tests, the paper further establishes that the tradable skewness factor commands a positive premium that is more sizeable and more significant than any of the risk factors thus far considered in the literature.

We document that traditional commodity risk factors cannot explain the excess returns generated by the skewness strategy, suggesting that skewness is not another proxy for the fundamentals of backwardation and contango in commodity futures. Our findings are thus in line with the literature on skewness preferences, and specifically provide evidence for investors with cumulative prospect theory preferences and selective hedging practices in commodity markets.

To gain better understanding of the reasons behind the pricing of skewness, we see it as interesting to study, in the spirit of Moskowitz *et al.* (2012), Asness *et al.* (2013) or Koijen *et al.* (2017), skewness profits and drawdowns across asset classes.

Appendix A. Description of the risk factors.

This table provides definitions and data sources for the risk factors utilized in the paper.

Name	Definition	Data source
Panel A: Baseline four-factor model		
EW	Excess return of equally-weighted long-only monthly-rebalanced portfolio of commodity futures	Datastream
TS	Excess return of long-short portfolio sorted by prior 12-month roll yield	Datastream
Mom	Excess return of long-short portfolio sorted by prior 12-month excess returns	Datastream
HP	Excess return of long-short portfolio double-sorted by prior 12-month speculators' and hedgers' hedging pressure	CTFC
Panel B: Other systematic risk factors		
Liquidity	Excess return of long-short portfolio sorted by prior 2-month dollar volume over absolute return	Datastream
ΔOI	Excess return of long-short portfolio sorted by changes in current total open interest along entire term structure	Datastream
Inflation β	Excess return of long-short porfolio sorted by β of 60-month regression of commodity futures returns on unexpected inflation	FED
Dollar β	Excess return of long-short porfolio sorted by β of 60-month regression of commodity futures returns on effective US dollar changes versus a basket of foreign currencies	FED
Value	Excess return of long-short portfolio sorted on value, defined as the ratio of the log of the average daily front-end futures prices from 4.5 to 5.5 years ago divided by the front-end log futures price at time t	Datastream
CV	Excess return of long-short portfolio sorted by variance-over-mean of daily futures returns over prior 36 months	Datastream
Panel C: Traditional risk factors motivated by the equity, fixed income and commodity literature		
S&P-GSCI	S&P-GSCI excess return index	Datastream
EqMkt	Excess value-weighted return of all CRSP US firms listed on the NYSE, AMEX, or NASDAQ	K.R. French's website
SMB	Small-minus-large or size factor (difference in returns between small and large capitalization stocks)	K.R. French's website
HML	High-minus-low or value factor (difference in returns between high and low book-to-market stocks)	K.R. French's website
UMD	Up-minus-down or equity momentum factor (difference in returns between winner and loser stocks)	K.R. French's website
Bond	Excess returns on the Barclays US Aggregate Bond Index	Bloomberg

Appendix B. Pairwise correlations among monthly factors.

The table reports Pearson correlation coefficients for the factors described in Table II and Table IV (Q1-Q5). Appendix A provides a detailed description of all the risk factors. Bold signifies significance at the 10% level or better. The sample observations for the estimation are monthly returns from January 1987 to November 2014.

	Baseline commodity pricing model				Augmented commodity pricing model						Traditional risk factors					
	EW	TS	Mom	HP	Liquidity	ΔOI	Inflation β	Dollar β	Value	CV	S&P-GSCI	EqMkt	SMB	HML	UMD	Bond
TS	**0.10**															
Mom	**0.14**	**0.30**														
HP	**0.11**	0.02	**0.29**													
Liquidity	0.05	**0.15**	-0.02	**-0.26**												
ΔOI	0.00	-0.08	**-0.17**	0.06	-0.05											
Inflation β	**0.19**	**0.24**	**0.14**	-0.08	**0.33**	-0.06										
Dollar β	**0.16**	**0.15**	0.01	**0.13**	0.05	-0.08	**0.16**									
Value	**-0.23**	**-0.30**	**-0.42**	**-0.31**	-0.01	0.08	**-0.33**	**-0.23**								
CV	0.11	**0.16**	**0.20**	**0.18**	-0.01	0.06	0.00	-0.08	**-0.20**							
S&P-GSCI	**0.74**	**0.23**	**0.21**	-0.07	**0.34**	-0.03	**0.47**	**0.29**	**-0.37**	**0.09**						
EqMkt	**0.26**	0.08	0.02	0.04	0.02	0.02	-0.02	**0.15**	-0.09	0.02	**0.17**					
SMB	**0.09**	**0.14**	**0.11**	**0.15**	-0.02	-0.02	0.04	**0.15**	**-0.15**	0.02	**0.11**	**0.26**				
HML	0.01	**-0.09**	0.02	-0.06	-0.01	**-0.14**	**0.09**	-0.05	-0.06	0.02	0.06	**-0.29**	**-0.30**			
UMD	-0.05	0.07	**0.20**	-0.05	0.08	0.02	**0.15**	0.02	-0.07	0.03	0.07	**-0.25**	0.04	-0.09		
Bond	0.01	-0.01	0.05	0.03	**-0.10**	-0.06	**-0.13**	0.02	**-0.11**	0.07	-0.03	**0.11**	**-0.14**	0.03	0.05	
Skewness	0.07	**0.21**	**0.10**	**0.15**	0.09	**-0.14**	**0.28**	**0.16**	**-0.16**	0.06	**0.16**	**-0.10**	**0.09**	-0.01	**0.12**	0.00

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Table I. Summary statistics for individual commodity time-series of skewness

This table summarizes per commodity the sequence of Pearson coefficients of skewness, Equation (1), obtained at each month-end *t* using daily data over the preceding *t*-11 to *t* window. It provides the mean, 25th quintile, median (50th quantile), 75th quintile and standard deviation. The sampling period is January 1987 to November 2014.

	T	Mean	StDev	25%	Median	75%
Panel A: Agricultural commodities						
Cocoa	335	0.0138	0.5245	-0.3079	0.1248	0.3355
Coffee	335	-0.0093	0.673	-0.3098	-0.0256	0.3314
Corn	335	-0.0190	0.3587	-0.2583	-0.0413	0.2527
Cotton	335	-0.0938	0.3231	-0.2489	-0.0911	0.0502
Oats	335	-0.0931	0.3057	-0.2919	-0.1269	0.1111
Orange juice	335	0.3687	1.3526	-0.3171	-0.0414	0.4672
Rough rice	178	0.0117	0.3684	-0.1372	0.0290	0.1986
Soybeans	335	-0.1705	0.263	-0.3605	-0.1473	0.0112
Soybean meal	335	0.0011	0.3428	-0.2281	-0.0058	0.2086
Soybean oil	335	0.1510	0.2817	-0.0406	0.1441	0.3433
Sugar	335	-0.1596	0.4004	-0.3954	-0.1061	0.0435
Wheat	335	0.0677	0.279	-0.1064	0.0941	0.2606
Panel B: Energy commodities						
Crude oil	335	-0.2461	0.8284	-0.3697	-0.1297	0.0828
Electricity	128	0.0880	0.3473	-0.1216	0.1472	0.299
Gasoline	335	-0.2716	0.6951	-0.385	-0.2202	0.0025
Heating oil	335	-0.2272	0.8497	-0.2984	-0.1017	0.077
Natural gas	295	0.0250	0.4151	-0.2346	-0.0038	0.2693
Panel C: Livestock commodities						
Feeder cattle	335	-0.1269	0.2751	-0.2134	-0.1062	0.0295
Frozen pork bellies	303	0.0915	0.5039	-0.0587	-0.0038	0.1053
Lean hogs	335	-0.0746	0.1788	-0.2025	-0.0922	0.0372
Live cattle	335	-0.0500	0.265	-0.1574	-0.0152	0.0984
Panel D: Metal commodities						
Copper	316	-0.1144	0.5333	-0.3018	-0.0059	0.2157
Gold	335	-0.3056	1.0287	-0.7974	-0.4286	0.0532
Palladium	335	-0.1998	0.4487	-0.4991	-0.2702	0.0987
Platinum	335	-0.2762	0.4287	-0.5504	-0.3338	-0.0933
Silver	335	-0.4321	0.5833	-0.8362	-0.3501	0.0115
Panel E: Lumber						
Lumber	335	0.0616	0.1554	-0.0337	0.0654	0.1320

Table II. Summary statistics for the risk factors

The table presents summary statistics for monthly risk factors over the sample January 1987 to November 2014. Panel A focuses on a baseline pricing model that includes a long-only equally-weighted portfolio of all commodities, as well as long-short portfolios based on signals that capture the backwardation and contango cycle. Panel B contains other long-short commodity-specific benchmarks that mimic systematic factors. Panel C presents traditional risk factors that emanate from the equity, bond and commodity pricing literature. Appendix A provides a detailed description of all the factors. Significance *t*-ratios for the annualized mean excess returns are shown in parentheses. Sharpe ratios are annualized mean excess returns (Mean) over annualized standard deviations (StDev). Omega ratios are the probability of gains divided by the probability of losses using 0% as threshold.

	Mean		StDev	Sharpe ratio	Omega ratio
Panel A: Baseline pricing model					
Equal-weighted portfolio (EW)	-0.0021	(-0.08)	0.1207	-0.0175	0.9861
Term structure (TS)	0.0463	(2.07)	0.1196	0.3873	1.3355
Momentum (Mom)	0.0895	(3.40)	0.1455	0.6153	1.5979
Hedging pressure (HP)	0.0578	(2.37)	0.1206	0.4796	1.4460
Panel B: Augmented commodity pricing model					
Liquidity	0.0114	(0.52)	0.1003	0.1133	1.0900
ΔOpen interest (ΔOI)	0.0032	(0.18)	0.0946	0.0338	1.0255
Inflation β	0.0296	(1.16)	0.1340	0.2208	1.1848
Dollar β	0.0127	(0.57)	0.1162	0.1093	1.0872
Value	0.0334	(1.44)	0.1201	0.2783	1.2320
Coefficient of variation (CV)	0.0318	(1.56)	0.0993	0.3207	1.2944
Panel C: Traditional risk factors					
S&P-GSCI	0.0352	(0.77)	0.1989	0.1768	1.1481
Equity index (EqMkt)	0.0814	(2.70)	0.1542	0.5275	1.4823
Size (SMB)	0.0025	(0.14)	0.1055	0.0236	1.0192
Value (HML)	0.0277	(1.23)	0.1010	0.2742	1.2482
Equity momentum (UMD)	0.0699	(2.15)	0.1621	0.4313	1.4667
Bond index	0.0336	(4.51)	0.0367	0.9156	1.9465

Table III. Relationship between skewness signal and other characteristics

The table summarizes the properties of skewness-based commodity quintiles from January 1987 to November 2014. Q1 is the quintile with the 20% lowest Sk_i commodities and Q5 the quintile with the 20% highest Sk_i commodities. The characteristics are measured over 12-month windows that are sequentially rolled forward one month at a time. The last column shows Newey-West *h.a.c.* *t*-statistics for the null hypothesis that there is no difference in a given characteristic across the Q1 and Q5 quintiles. Panel B shows the characteristics related with backwardation and contango phases such as the roll-yield, excess return, hedgers' hedging pressure and speculators' hedging pressure signals. Bold font denotes significant at the 10% level or better. The sampling period is January 1987 to November 2014.

	Q1	Q2	Q3	Q4	Q5	Q1-Q5	
Panel A: Pre-ranking skewness	-0.7294	-0.2596	-0.0707	0.0978	0.5407	**-1.27**	(-17.73)
Panel B: Backwardation versus contango characteristics							
Roll-yield	-0.0008	-0.0034	-0.0060	-0.0094	-0.0105	**0.01**	(5.29)
Excess return	2.91%	0.57%	0.78%	-1.90%	-1.86%	**4.77%**	(1.75)
Hedgers' hedging pressure	0.3969	0.4295	0.4389	0.4417	0.4531	**-0.06**	(-6.10)
Speculators' hedging pressure	0.6570	0.6387	0.6198	0.5974	0.5848	**0.07**	(5.97)

Table IV. Performance of skewness quintiles and long-short portfolios

This table summarizes the performance of the long-only portfolios containing the 20% most negative-skew commodities (Q1) to the 20% most positive-skew (Q5) commodities, and the low-minus-high fully-collateralized skewness portfolio that longs Q1 and shorts Q5. The underlying signal is the Pearson's *moment of skewness* of the daily returns measured over a ranking period of 12 months. Panel A summarizes the portfolio monthly return distribution. Mean denotes annualized average excess return, StDev annualized standard deviation, Sharpe ratio is Mean divided by StDev, Sortino ratio is Mean divided by annualized downside volatility and Omega ratio measures the probability of gains over probability of losses. Panel B presents annualized alphas and beta coefficients with Newey-West *t*-statistics in parentheses (bootstrap *p*-values for alphas in brackets) from regressions of the excess returns of skewness portfolios on the average commodity factor (*EW*), term structure factor (*TS*), momentum factor (*Mom*) and hedging pressure factor (*HP*); details on the construction of the factors are provided in Section 3.2.1. Bold font denotes significant at the 10% level or better. The sample period is January 1987 to November 2014.

	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q1-Q5**
Panel A: Summary statistics						
Mean	0.0512	0.0401	-0.0020	-0.0277	**-0.1089**	**0.0801**
	(1.42)	(0.99)	(-0.06)	(-0.80)	(-3.35)	(3.83)
StDev	0.1748	0.1755	0.1715	0.1647	0.1596	0.1020
Post-ranking skewness	-0.1006	-0.0774	-0.0102	-0.0165	-0.0247	-0.0760
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	55.25%	55.56%	48.46%	50.62%	41.05%	59.26%
Maximum drawdown	-0.4244	-0.6006	-0.7300	-0.8205	-0.9731	-0.2973
Sharpe ratio	0.2932	0.2287	-0.0114	-0.1683	-0.6820	0.7848
Sortino ratio (0%)	0.1266	0.0910	-0.0045	-0.0632	-0.2375	0.4017
Omega ratio (0%)	1.2547	1.1985	0.9915	0.8792	0.5969	1.8136
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)
	{0.08}	{0.02}	{0.31}	{0.19}	{0.00}	{0.00}
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^2	49.12%	56.57%	52.79%	56.87%	45.21%	5.66%

Table V. Robustness checks for performance of long-short skewness portfolios

The table studies the abnormal performance of various long-short skewness (Q1-Q5) portfolios. Panel A uses as signal the skewness of the residuals from time-series regressions of daily commodity futures returns on daily observations for the *EW*, *TS*, *Mom* and *HP* factors, business cycle indicators and/or calendar-month dummies. Panel B uses as alternative pricing models *i*) a four-factor equation comprising the excess returns of the S&P-GSCI, *TS*, *Mom* and *HP* portfolios, *ii)* the baseline four-factor equation augmented with systematic risk factors, and *iii*) equations motivated from the equity/bond pricing literature. Panel C excludes from the cross-section the 80% of futures contracts with lowest liquidity according to the Amihud *et al.* (1997) measure, and deducts transaction costs of 0.066% per trade. The abnormal performance is measured as the annualized alpha (α) modeled in reference to the baseline four-factor model, except in Panel B where alternative pricing models are used in place. Newey-West t-statistics for the alphas are reported in parentheses and bootstrap p-values are in curly brackets. Appendix A provides a detailed description of all the factors. Bold denotes significance at the 10% level or better. The sampling period is January 1987 to November 2014.

	α	***t*-stat**	***p*-value**
Panel A: Signal used to construct the skewness risk factor			
EW, TS, HP, Mom-filtered returns	**0.0673**	(3.92)	{0.00}
Business cycle-filtered returns	**0.0386**	(1.94)	{0.03}
Calendar month dummy-filtered returns	**0.0518**	(2.51)	{0.01}
Risk factor, business cycle and dummy-filtered	**0.0383**	(2.07)	{0.02}
Panel B: Choice of asset pricing model			
S&P-GSCI, TS, Mom, HP	**0.0647**	(3.53)	{0.00}
Baseline pricing model augmented with systematic risk factors			
Liquidity	**0.0637**	(3.51)	{0.00}
ΔOI	**0.0681**	(3.67)	{0.00}
Inflation β	**0.0602**	(3.36)	{0.00}
Dollar β	**0.0652**	(3.54)	{0.00}
Value	**0.0702**	(3.71)	{0.00}
CV	**0.0658**	(3.61)	{0.00}
All risk factors	**0.0581**	(3.20)	{0.00}
Traditional commodity, equity and fixed income pricing models			
Carhart (1997), Bond index	**0.0873**	(3.59)	{0.00}
Carhart (1997), Bond, Commodity risk factors	**0.0765**	(3.52)	{0.00}
Panel C: Iliquidity and transaction costs			
80% most liquid contracts	**0.0512**	(2.80)	{0.01}
T-costs = 0.066%	**0.0624**	(3.40)	{0.00}

Table VI. Cross-sectional pricing ability of skewness factor

The table reports average coefficients from pass-two Fama-MacBeth cross-sectional regressions of excess commodity futures returns on factor loadings or betas, where we augment the baseline four-factor model, Model A, with systematic risk factors. The test assets are the 27 individual commodities. Shanken (1992) *t*-statistics are reported in parentheses. Appendix A provides a detailed description of all the factors. Bold means significant at the 10% level or better. The sample period is January 1987 to November 2014.

	Model A		Model B		Model C		Model D		Model E		Model F		Model G		Model H	
Intercept	-0.0020	-0.0016	-0.0015	-0.0016	-0.0020	-0.0016	-0.0028	**-0.0030**	-0.0024	-0.0020	-0.0019	-0.0020	-0.0022	-0.0019	-0.0008	-0.0012
	(-1.12)	(-0.92)	(-0.84)	(-0.89)	(-1.14)	(-0.90)	(-1.57)	(-1.67)	(-1.32)	(-1.09)	(-0.98)	(-1.04)	(-1.21)	(-1.08)	(-0.40)	(-0.59)
Skewness		**0.0040**		**0.0040**		**0.0034**		**0.0043**		**0.0042**		**0.0044**		**0.0045**		**0.0046**
		(2.42)		(2.48)		(2.10)		(2.62)		(2.57)		(2.49)		(2.70)		(2.62)
EW	0.0027	0.0025	0.0024	0.0027	0.0029	0.0026	**0.0037**	**0.0041**	0.0033	0.0030	0.0028	0.0031	0.0031	0.0030	0.0024	0.0029
	(1.34)	(1.26)	(1.20)	(1.35)	(1.46)	(1.31)	(1.87)	(2.01)	(1.64)	(1.51)	(1.32)	(1.49)	(1.55)	(1.51)	(1.07)	(1.27)
TS	-0.0002	0.0003	-0.0006	0.0000	0.0002	0.0006	0.0001	0.0006	0.0007	0.0008	0.0003	0.0004	0.0002	0.0005	0.0008	0.0013
	(-0.11)	(0.16)	(-0.35)	(-0.02)	(0.09)	(0.35)	(0.08)	(0.32)	(0.42)	(0.46)	(0.16)	(0.22)	(0.09)	(0.26)	(0.43)	(0.67)
Mom	**0.0039**	**0.0038**	0.0031	0.0034	**0.0042**	**0.0042**	0.0035	**0.0039**	**0.0044**	**0.0042**	0.0036	0.0034	**0.0038**	**0.0038**	**0.0051**	**0.0052**
	(1.82)	(1.76)	(1.47)	(1.54)	(1.97)	(1.95)	(1.60)	(1.72)	(2.03)	(1.93)	(1.57)	(1.45)	(1.75)	(1.73)	(2.16)	(2.19)
HP	**0.0033**	**0.0035**	**0.0031**	**0.0031**	**0.0031**	**0.0031**	**0.0036**	**0.0035**	**0.0034**	**0.0038**	**0.0034**	**0.0033**	**0.0039**	**0.0040**	**0.0037**	**0.0037**
	(1.86)	(1.93)	(1.76)	(1.72)	(1.75)	(1.72)	(1.96)	(1.88)	(1.90)	(2.06)	(1.80)	(1.68)	(2.18)	(2.15)	(1.88)	(1.82)
Liquidity			0.0012	0.0014											0.0017	0.0019
			(0.76)	(0.86)											(0.97)	(1.06)
ΔOI					0.0004	0.0010									0.0011	0.0009
					(0.31)	(0.70)									(0.72)	(0.57)
Inflation β							0.0031	0.0028							0.0033	0.0033
							(1.51)	(1.37)							(1.57)	(1.52)
Dollar β									0.0005	0.0004					0.0001	0.0004
									(0.26)	(0.24)					(0.06)	(0.19)
Value											**0.0041**	**0.0040**			**0.0038**	**0.0038**
											(2.05)	(1.98)			(1.90)	(1.90)
CV													0.0023	0.0022	0.0022	0.0024
													(1.46)	(1.37)	(1.31)	(1.38)
Adjusted R^2	25.82%	29.68%	29.82%	33.54%	30.32%	33.65%	30.99%	34.25%	29.70%	33.26%	29.94%	34.18%	30.39%	33.71%	47.17%	49.80%

Table VII. Cross-sectional robustness tests

The table tests the robustness of the cross-sectional Fama-MacBeth estimation results to the signal used for the construction of the tradeable skewness factor (Panel A), to the choice of pricing models (Panel B) and to the use of commodity characteristics in place of sensitivities to the risk factors in the cross-sectional regression (Panel C). The table reports the average skewness premium, $\hat{\lambda}_S$; *t*-statistic for its significance using a Shanken-adjustment in Panels A and B and Newey and West-adjustment in Panel C; the explanatory power of the pricing model at hand and of the same model without the skewness factor. The pricing model in Panel A is the baseline four-factor (*EW*, *TS*, *Mom* and *HP*) model. Appendix A provides a detailed description of all the factors. Bold font indicates significance at the 10% level or better. The sample covers the period from January 1987 to November 2014.

			Adjusted R^2	
	$\hat{\lambda}_S$	*t*-statistic	with skewness	without skewness
Panel A: Signal used to construct the skewness factor				
EW, TS, HP, Mom-filtered returns	**0.0042**	(2.80)	28.78%	25.82%
Business cycle-filtered returns	**0.0035**	(2.02)	29.66%	25.82%
Calendar month dummy-filtered returns	**0.0033**	(2.04)	30.19%	25.82%
Panel B: Other pricing models				
S&P-GSCI, TS, Mom, HP	**0.0039**	(2.40)	29.59%	25.93%
Carhart (1997), Bond index	**0.0048**	(2.64)	29.43%	23.54%
Carhart (1997), Bond, Baseline commodity factors	**0.0057**	(3.20)	42.21%	38.63%
Panel C: Pricing model based on characteristics				
Baseline characteristic model	**-0.0088**	(-3.59)	10.19%	9.04%
Baseline characteristic model augmented with systematic signals				
Liquidity	**-0.0083**	(-3.37)	8.98%	7.72%
ΔOI	**-0.0093**	(-3.67)	10.30%	9.19%
Inflation β	**-0.0085**	(-2.90)	15.26%	14.09%
Dollar β	**-0.0089**	(-3.28)	14.24%	12.48%
Value	**-0.0083**	(-3.41)	15.04%	13.64%
CV	**-0.0078**	(-2.95)	11.40%	10.13%
All systematic signals	**-0.0076**	(-2.38)	22.05%	20.16%

Figure 1. Skewness of daily commodity futures returns over 12-month rolling windows

This figure plots the Pearson moment of skewness of the distribution of daily commodity futures returns on each month end *t* using data over the preceding *t*-11 to *t* window. The two horizontal lines are the 95% confidence bands to test the hypothesis that skewness is zero. The plotted lines pertain to four representative commodities pertaining to different sectors. The legend reports the percentage of months for each commodity when the skewness is significantly positive or negative. The sampling period is January 1987 to November 2014.

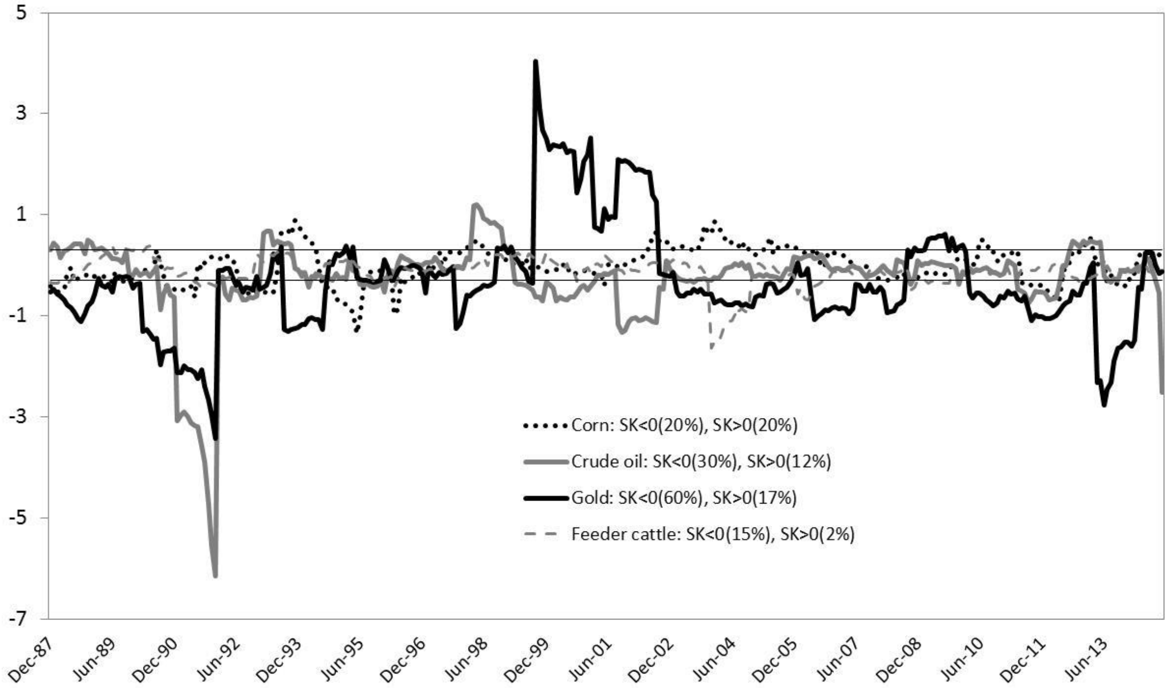

Figure 2. Cumulative log returns of skewness-based commodity portfolios

The figure plots the cumulative log return of five portfolios: quintiles Q1 to Q5 formed according to the Pearson's moment of skewness Sk_i signal measured at the end of each month with the daily returns in the most recent 12-month window. Q1 contains the 20% of commodities with the lowest $\widehat{Sk}_i$ values and Q5 contains the 20% of commodities with the highest $\widehat{Sk}_i$ values. The sampling period is January 1987 to November 2014.

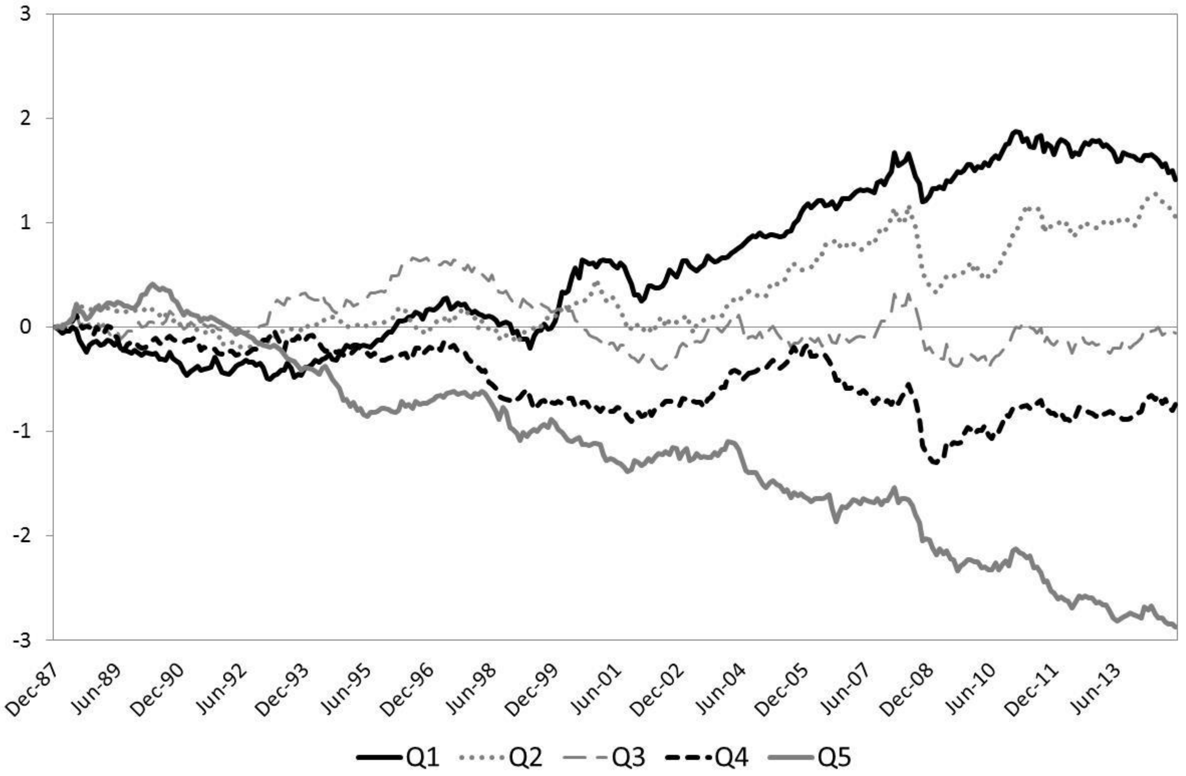

Figure 3. Frequency of commodities in long Q1 and short Q5 commodity portfolios

The graph shows the percentage of months over the entire sample period from January 1987 to November 2014 (*T*=324 months in total) that each commodity enters the long (most-negatively-skew Q1) portfolio and short (most-positively-skew Q5) portfolio. For instance, cocoa is a constituent of Q1 during 66 months (20.37%), Q5 during 124 months (38.27%), and does not enter any portfolio, long or short, during the remaining 134 months (41.36%).

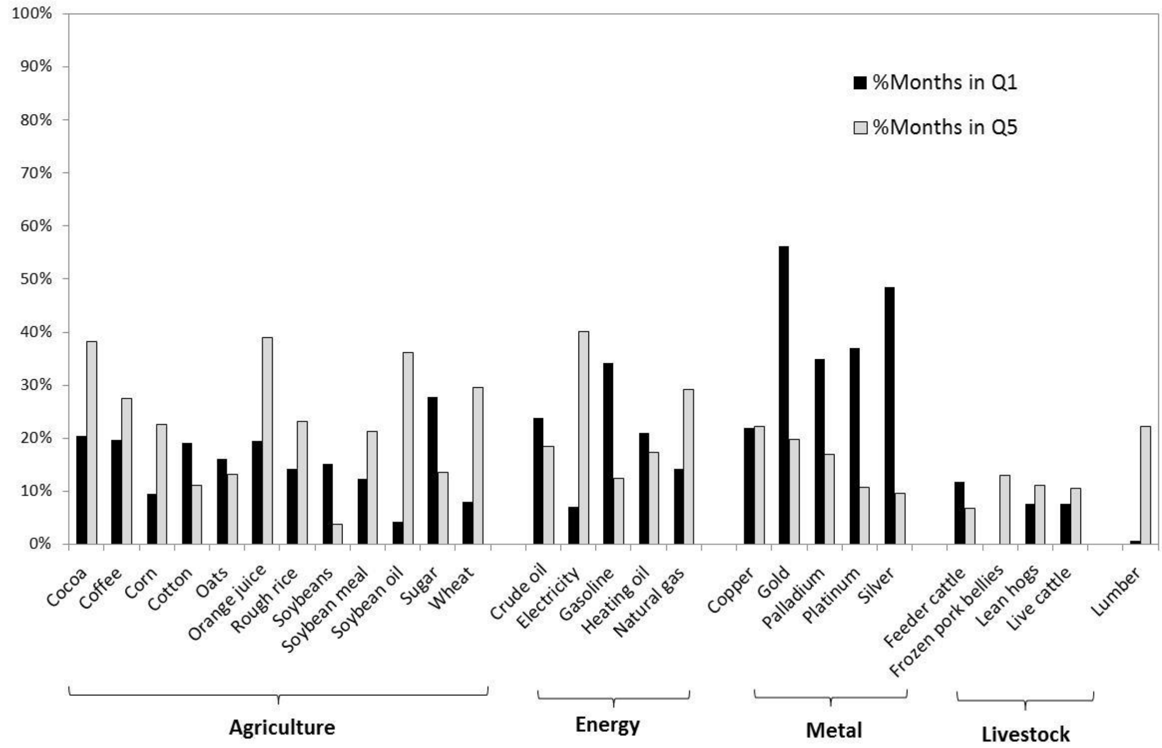

Figure 4. Conditional alpha of commodity skewness strategy

The graph shows the sequential annualized alpha of the long-short skewness strategy based on seven-year rolling regressions. The strategy buys the most negative-skew quintile Q1 and shorts the most positive-skew quintile Q5 at the end of each month each seven-year window. The discontinuous lines are the upper limit and lower limit of the 95% confidence band based on Newey-West standard errors.

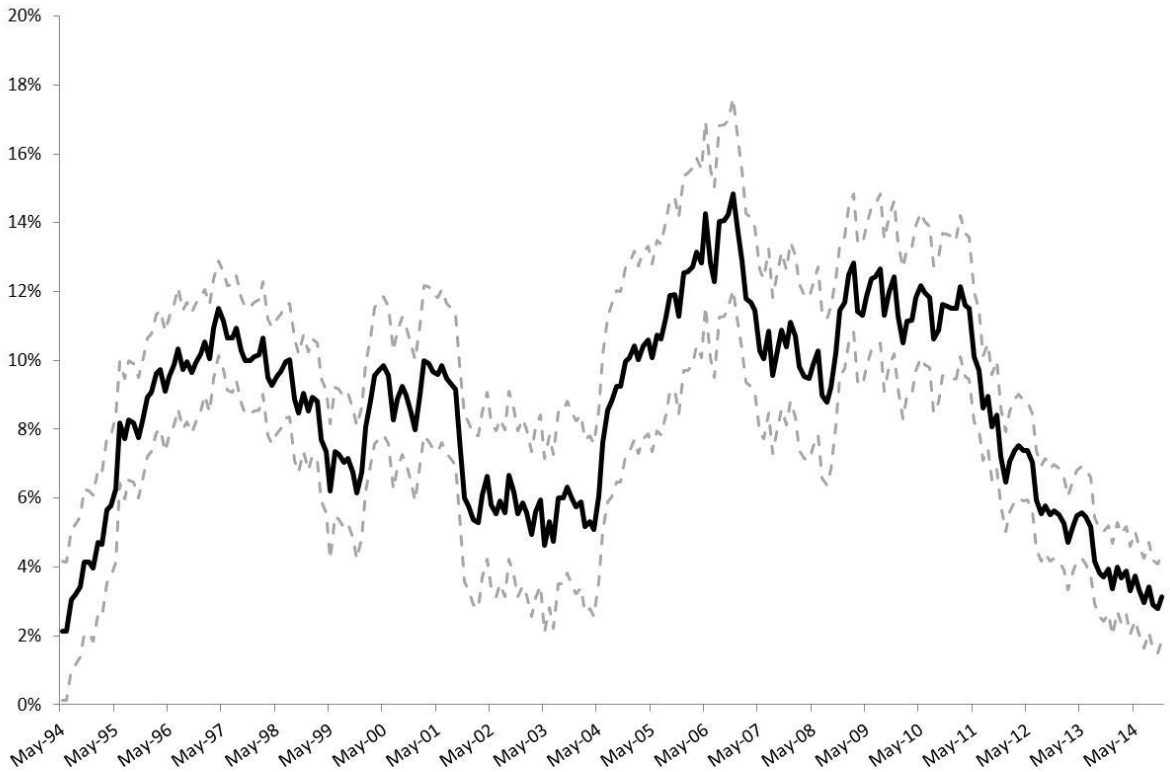

Figure 5. Conditional price of skewness factor

The figure shows the conditional lambda of the skewness factor in Equation (6) based on seven-year rolling estimation windows for 27 individual commodities (Model A in Table VI). The discontinuous lines are the upper limit and lower limit of the 95% confidence band based on Shanken standard errors.