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Is Idiosyncratic Volatility Priced in Commodity Futures Markets?

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Abstract

This article investigates the relationship between expected returns and past idiosyncratic volatility in commodity futures markets. Measuring the idiosyncratic volatility of 27 commodity futures contracts with traditional pricing models that fail to account for backwardation and contango leads to the puzzling finding that idiosyncratic volatility is significantly negatively priced cross-sectionally. However, idiosyncratic volatility is not priced when the phases of backwardation and contango are suitably factored in the pricing model. A time-series portfolio analysis similarly suggests that failing to recognize the fundamental risk associated with the inexorable phases of backwardation and contango leads to overstated profitability of the idiosyncratic volatility mimicking portfolios.

JEL classifications: G13; G14.

Keywords: Commodity futures; Idiosyncratic volatility; Backwardation; Contango.

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1. Introduction

The pricing of commodity futures contracts is informed by the theory of storage of Kaldor (1939), Working (1949) and Brennan (1958) and the hedging pressure hypothesis of Keynes (1930), Cootner (1960) and Hirshleifer (1988). Various trading strategies that empirically validate the predictions from these theories have been shown to generate attractive performance by systematically buying backwardated contracts with high roll-yields, scarce supply, net short hedgers, net long speculators and good past performance, and shorting contangoed contracts with low roll-yields, abundant supply, net long hedgers, net short speculators and poor past performance (Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006; Miffre and Rallis, 2007; Gorton *et al.*, 2012; Basu and Miffre, 2013, Szymanowska *et al.*, 2014; Bakshi *et al.*, 2015). Additional signals that have been shown to generate significant spreads in commodity futures returns are associated with value, liquidity, skewness or total volatility (Gorton *et al.*, 2012; Asness *et al.*, 2013; Szymanowska *et al*., 2014; Fernandez-Perez *et al*., 2016).

The contributions of this article are threefold. First, it contributes to the commodity pricing literature by testing whether idiosyncratic volatility has information content about future returns. At least theoretically, idiosyncratic volatility should matter in a world with trading costs and non-marketability of producers claims (Hirshleifer, 1988). Yet, the extant empirical implementations of Hirshleifer's (1988) theoretical model (*e.g.*, Bessembinder, 1992; Rouwenhorst and Tang, 2012) do not generally endorse idiosyncratic volatility as a driver of commodity futures prices. A potential pitfall of these studies is that, in line with Hirshleifer's (1988) framework, they extract idiosyncratic volatility via the CAPM or a traditional multifactor model; thus, they fail to explicitly account for the fundamentals of backwardation and contango that have been shown in the last decade to be fundamental to the pricing of commodity futures contracts.[1] These findings warrant a reassessment of the evidence on the role of idiosyncratic volatility in commodity futures markets using pricing models that explicitly account for backwardation and contango (Basu and Miffre, 2013; Bakshi *et al*., 2015).

Our second contribution is to replicate in the novel context of commodity futures markets the methodology deployed in two-widely cited papers, Ang *et al.* (2006, 2009), to determine whether their findings for US/international stocks extend to other markets.[2] Ang *et al.* (2006, 2009) provocatively documented that stocks with higher idiosyncratic volatility present significantly poorer performance; namely, idiosyncratic volatility of equities is puzzlingly negatively priced. Establishing that the same pattern applies to financial markets other than (US and international) equities can be seen, following the reasoning of Ang *et al.* (2009), as suggesting that there is an underlying economic source behind the phenomenon. While faithfully replicating their methodology, we do find also a significantly negative pricing of idiosyncratic volatility in commodity futures markets, however, it vanishes when the fundamentals of backwardation and contango are suitable factored in the pricing model.

Our third contribution relates to exploring the reasons as to why idiosyncratic volatility may appear negatively priced in commodity futures markets. Expected idiosyncratic skewness, lagged returns and financial distress (Boyer *et al.*, 2010; Huang *et al.*, 2010; Avramov *et al.*,

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[1] Hirshleifer (1988) decomposes the commodity futures risk premium into two components: the first one depends on the CAPM beta, the second one on the idiosyncratic volatility of the contract and net hedging. While Bessembinder (1992) validates the predictions of Hirshleifer's (1988) model, Rouwenhorst and Tang (2012) refute the idea that idiosyncratic volatility conditional on net hedging matters to the pricing of commodities.

[2] Theoretically, since idiosyncratic volatility can be diversified away, it is not priced (Sharpe, 1964) or there could be a positive link since poorly-diversified agents demand incremental returns for bearing idiosyncratic risk (Merton, 1987; Malkiel and Xu, 2002). Empirically, the evidence is inconclusive. Some studies support the contention that idiosyncratic volatility does not matter (Fama and McBeth, 1973; Bali *et al.*, 2005; Bali and Cakici, 2008; Huang *et al.*, 2010; Han and Lesmond, 2011; Fink *et al.*, 2012). Other articles report evidence in favor of a positive (Malkiel and Xu, 2002; Goyal and Santa-Clara, 2003; Fu, 2009) or a negative association (Ang *et al*., 2006, 2009; Guo and Savickas, 2008, 2010; Jiang et al., 2009; Chabi-Yo et al., 2011) between idiosyncratic volatility and expected returns. Differences in asset pricing model, weighting scheme, methodology, data set and time period have been put forward as possible explanations for the diverging evidence. Meanwhile, a parallel literature (Campbell *et al.*, 2001; Xu and Malkiel, 2003; Brandt *et al*., 2010) has studied the time-series behavior of stock idiosyncratic volatility.

2012) have been adduced as explanations for the puzzling finding of Ang *et al.* (2006, 2009) that idiosyncratic volatility is negatively priced in equity markets. Whenever pertinent (and feasible) we test whether these factors account for the pricing of idiosyncratic volatility in commodity futures markets. Our evidence suggests that, rather, the pricing of idiosyncratic volatility is an artifact of neglecting the fundamentals of backwardation and contango. This finding is not surprising in the light of evidence that suggests that the backwardation/contango cycle acts both as a priced risk factor in equity markets and as a leading indicator of future economic activity (*e.g.*, Baker and Routledge, 2012; Koijen *et al.*, 2013; Bakshi *et al.*, 2015; Fernandez-Perez *et al.*, 2015; Brooks *et al.*, 2016).

Using both a two-pass Fama and MacBeth (1973) regression framework and a factor mimicking portfolio approach, we show that the pricing of idiosyncratic volatility in commodity futures markets crucially hinge on the choice of benchmark used to extract the idiosyncratic volatility signal. In the context of traditional pricing models that fail to recognize the fundamentals of backwardation and contango in commodity futures markets, the results suggest that *i*) idiosyncratic volatility is negatively priced cross-sectionally, and *ii*) idiosyncratic volatility mimicking portfolios that over time buy low idiosyncratic volatility commodities and short high idiosyncratic volatility commodities offer sizeable alpha. These results are aligned with those reported by Ang *et al.* (2009) for international equity markets. By contrast, in the context of pricing models that acknowledge the backwardation/contango dynamics of commodity futures markets, the statistical tests suggest that idiosyncratic volatility is not cross-sectionally priced, and idiosyncratic volatility mimicking portfolios deliver insignificant alpha. This outcome agrees with the theoretical wisdom that idiosyncratic volatility of financial assets can be diversified away and hence, it is not priced. The conclusions are robust to the inclusion in the various pricing models of factors such as expected idiosyncratic skewness or past returns that have been shown to explain the puzzling negative pricing of idiosyncratic volatility in equity markets. The negative pricing of idiosyncratic volatility of commodity futures measured with traditional benchmarks is not an artifact of neglecting illiquidity risk either. Altogether the evidence suggests that idiosyncratic volatility measured with traditional pricing models proxies for a missing risk factor that relates to the inexorable phases of backwardation and contango.

The remainder of the paper is structured as follows. Section 2 presents the two-pass Fama and MacBeth (1973) and factor-mimicking portfolio approaches. Section 3 describes the commodity futures data and motivates the two types of benchmarks used to extract the idiosyncratic volatility signal. Section 4 discusses the findings before concluding in Section 5.

2. Methodology

To study the relationship between idiosyncratic volatility and expected returns in commodity futures markets, we deploy two approaches: first, the two-pass Fama and MacBeth (1973) regression framework typically known as "cross-sectional tests"; second, a time-series factor mimicking portfolio approach. Since our goal is to assess the impact of the choice of benchmark on the inferred relationship, we deploy both approaches using different benchmarks.

2.1. Cross-sectional tests

Our first tests are based on Ang *et al*.'s (2009) methodology to analyze the relation between equity returns and lagged idiosyncratic volatility. Theirs is, in fact, a close version of the two-pass Fama and MacBeth (1973) methodology. In our exposition, bold font denotes vectors. At the first stage, for each commodity $i = 1,2,\ldots,N$ in the sample we estimate the following time-series regression sequentially using windows that comprise D daily observations

$$r_{i,d} = \alpha_i + \boldsymbol{\beta}_i'\boldsymbol{f}_d + \varepsilon_{i,d}\,, \quad d = 1,\ldots,D \text{ days} \tag{1}$$

where $r_{i,d}$ is the excess return of the i^{th} commodity on day d; the $K \times 1$ regressor vector $\boldsymbol{f}_d$ gathers the K factor risk premia associated with the chosen benchmark on day d; $\varepsilon_{i,d}$ is an innovation and $(\alpha_i, \boldsymbol{\beta}_i')'$ is the unknown parameter vector estimated sequentially by OLS using as sample the D days spanned by the corresponding window (or ranking period of length R in months). Accordingly, we measure the idiosyncratic volatility of each commodity at the end of month t, which we denote $\widehat{IVol}_{i,[t-R:t]}$, as the standard deviation of the residuals of regression (1) estimated using the daily data comprised within months $t - R$ to t for $R = \{1, 3, 6, 12\}$.

At the second stage, on each month $t + 1$ in the sample period we estimate the following cross-section regression by OLS using data on all N sampled commodities

$$r_{i,t+1} = \lambda_{0,t+1} + \lambda_{IVol,t+1}\widehat{IVol}_{i,[t-R:t]} + \boldsymbol{\lambda}_{t+1}'\widehat{\boldsymbol{\beta}}_{i,t+1} + \upsilon_{i,t+1} \text{ , } i = 1,2, \ldots\ldots N \qquad (2)$$

where $r_{i,t+1}$ is the month $t + 1$ excess return of the i^{th} commodity; $\widehat{IVol}_{i,[t-R:t]}$ is the past idiosyncratic volatility of the i^{th} commodity measured at stage one; $\widehat{\boldsymbol{\beta}}_{i,t+1}$ are the betas contemporaneous to the dependent variable which are obtained by OLS estimation of equation (1) using the daily observations within month $t + 1$; and $\upsilon_{i,t+1}$ is an innovation. At this second step we thus obtain a sequence of monthly $(K + 1) \times 1$ vectors of prices of risk, $(\hat{\lambda}_{IVol,t+1}, \hat{\boldsymbol{\lambda}}_{t+1}')'$, for each ranking period R of choice. The relevant risk price vector estimate, is the average of all the sequential cross-section estimates, $(\hat{\lambda}_{IVol}, \hat{\boldsymbol{\lambda}}')'$, and we similarly construct the corresponding cross-section average adjusted-R^2. As it is standard in a two-pass Fama and McBeth (1973) asset pricing approach such as this, the significance t-statistics for $(\hat{\lambda}_{IVol}, \hat{\boldsymbol{\lambda}}')'$, are computed using Shanken's (1992) error-in-variables consistent standard errors.

2.2. Time-series tests

The time-series tests are based on a factor mimicking portfolio construction approach. Following also the methodology deployed by Ang *et al.* (2006, 2009) in the context of stocks, at each month end t, we sort commodities into quintiles based on their idiosyncratic volatility, $\widehat{IVol}_{i,[t-R:t]}$, measured as the standard deviation of the residuals of regression (1) estimated with the daily observations in the window from month $t - R$ to t. We then construct an idiosyncratic volatility mimicking portfolio that buys the quintile with the lowest $\widehat{IVol}_{i,[t-R:t]}$ and shorts the quintile with the highest $\widehat{IVol}_{i,[t-R:t]}$. We hold the long-short portfolio for one month, at which time the same process is repeated to obtain a new idiosyncratic volatility portfolio.

As is standard in the commodity pricing literature (*e.g.*, Erb and Harvey, 2006), the portfolio constituents are equally-weighted with end-of-month rebalancing. The positions are fully-collateralized which amounts to setting the excess return of the long-short portfolio equal to half that of the long portfolio minus half that of the short portfolio.

3. Data on commodity futures and factor risk premia

Aside from describing the commodity futures data, this section motivates the choice of benchmarks used to extract idiosyncratic volatility, explains the methodology employed to construct the long-short commodity benchmarks and presents statistics of their performance. The data are obtained from *Datastream International*, Kenneth French's web library and *Bloomberg*. Our analysis begins on January 3, 1989, as dictated by the first daily observation available for the excess returns on Barclays' bond index, and ends on December 31, 2013.

3.1. Commodity futures data

Our data comprise daily settlement futures prices on 27 commodities from distinct sectors: 12 agricultural (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 (electricity, gasoline, heating oil n° 2, light sweet crude oil, natural gas), 4 livestock (feeder cattle, frozen pork bellies, lean hogs, live cattle), 5 metal (copper, gold, palladium, platinum, silver), and random length lumber. In order to mitigate illiquidity problems, commodity futures returns are constructed by holding the nearest-to-maturity contract up to one month before maturity and then rolling to the

2^{nd} nearest contract. In addition, using Amihud *et al.*'s (1997) approach we further test in Section 4 whether the pricing of idiosyncratic volatility is driven by illiquidity.

3.2. Traditional and long-short commodity benchmarks

The article studies the influence of the choice of benchmark on the relationship between idiosyncratic volatility and expected returns in commodity futures markets. Accordingly, we employ two types of benchmarks. The first set of benchmarks is inspired by the traditional asset pricing literature ("traditional" benchmarks, hereafter). The second set of benchmarks emanates from the commodity pricing literature ("long-short" commodity benchmarks, hereafter) and accordingly, the pricing models include factors meant to capture the fundamentals of backwardation and contango; as such, they are better suited at pricing commodity futures and thus, at extracting the idiosyncratic volatility signal.

The traditional benchmarks follow the spirit of Hirshleifer (1988) who ascribes a role to idiosyncratic volatility in commodity futures markets using an augmented version of the CAPM of Sharpe (1964). We follow his lead by framing our discussion within the traditional asset pricing literature, beginning the analysis with a simple commodity-based market model which we subsequently augment with stylized factors emanating from the traditional asset pricing literature. The traditional benchmarks employ as factor risk premia the excess return on the Standard and Poor's Goldman Sachs Commodity Index (S&P-GSCI) alone or in combination with the excess value-weighted return of all CRSP US firms listed on the NYSE, AMEX, or NASDAQ (Rm-Rf), the excess returns on the Barclays U.S. Aggregate Bond Index (Barclays), the size premium (small-minus-big or SMB), the value premium (high-minus-low or HML) or the excess returns on an equity momentum portfolio (up-minus-down or UMD).

Motivated by the theories of storage and hedging pressure, the second set of "long-short" commodity benchmarks incorporate risk premia designed to capture the fundamentals of backwardation and contango. The price of commodity futures in backwardation is expected to rise as maturity approaches; backwardation typically occurs when the term structure of commodity futures prices is downward-sloping and roll-yield[3] is positive, when hedgers are net short and speculators are net long or when past performance is good. Vice versa, the commodity futures price in contango is expected to drop so all the above signals are reversed. Accordingly, we construct the following three long-short commodity risk premia. The term structure (TS) portfolio buys the 20% of contracts with the most downward-sloping term structures or highest roll-yields and shorts the 20% of contracts with the most upward-sloping term structures or lowest roll-yields (see, *e.g.*, Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006). The hedging pressure (HP) portfolio buys the 20% of contracts for which hedgers are the shortest and speculators the longest[4] and sells the 20% of contracts for which hedgers are the longest and speculators the shortest (Basu and Miffre, 2013).[5] Finally, the momentum (Mom) portfolio, buys the 20% of contracts with the best past performance and sells the 20% of contracts with the worst past performance (Miffre and Rallis, 2007). The ranking period over which the three signals are averaged is 12 months, and the holding period is 1 month throughout.[6] As with the idiosyncratic volatility portfolio, the constituents of the TS, HP and Mom portfolios are equally-weighted with end-of-month rebalancing[7] and the positions are fully-collateralized.

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[3] Roll-yield at time *t* is the differential logarithmic price at *t* of the front and second-nearest contracts.
[4] Large traders report to the CFTC whether they are hedgers or speculators and whether they are long or short. Using the CFTC reports we calculate two hedging pressure measures – that of speculators and that of hedgers – where each is defined as the fraction of long positions relative to long and short positions. A low hedgers' hedging pressure indicates net short hedging and a high speculators' hedging pressure hits toward net long speculation; both are treated as signs of backwardation. Contango is signaled by high hedgers' hedging pressure and low speculators' hedging pressure.
[5] While extant studies use the positions of large hedgers (*e.g.*, de Roon *et al.*, 2000) or large speculators (*e.g.*, Carter *et al.*, 1983; Bessembinder, 1992), we consider both (as Basu and Miffre, 2013) to account for the influence of small traders. Thus, we use a double-sorting according to hedgers' hedging pressure with the 50th quantile as breakpoint, and then speculators' hedging pressure using the 40th quantile.
[6] A long ranking period of 12 months is pertinent for the TS, HP and Mom commodity risk premia in order to accommodate the fact that inventory levels are slow to replenish or deplete, making it unlikely for futures markets to switch more frequently between backwardation and contango.
[7] Daily returns for the long and short commodity portfolios are obtained by re-balancing the portfolio's weights to $1/N$ on the 1st trading day of each month and by letting the weights evolve naturally until the last day of the month, that is, $w_{i,t} = w_{i,t-1} \cdot (1 + r_{i,t-1})$ where $r_{i,t}$ is the day *t* return of the *i*th commodity and $w_{i,t}$ is its

3.3. Summary statistics for the factor risk premia

Table 1 summarizes the performance of the various factor risk premia. Panel A focuses on the risk premia that emanate from the traditional asset pricing literature and Panel B on the long-short commodity risk premia. The Sharpe ratios of the long-short commodity portfolios range from 0.41 to 0.51 with an average at 0.46, whereas that of the long-only S&P-GSCI merely stands at 0.02. This reinforces the well-documented fact that investors benefit from taking long positions in backwardated markets and short positions in contangoed markets.

[Insert Table 1 around here]

Table 2 presents the pairwise correlations (and significance *p*-values) for the various factor risk premia considered in our analysis. The correlations are low, ranging from -0.26 to 0.37, suggesting that multicollinearity is not an issue. The pairwise correlations between the TS, HP and Mom portfolio returns are positive, ranging from 0.21 to 0.37, in line with the fact that the three risk premia act as proxies for the fundamentals of backwardation and contango.

[Insert Table 2 around here]

4. Empirical Results

This section presents the results of our investigation of the pricing of idiosyncratic volatility in commodity futures markets using the two methodologies described in the previous section.

4.1. Cross-sectional results

Table 3 reports the prices of risk estimates, significance *t*-statistics and adjusted-R^2 obtained with traditional benchmarks (Panel A) and long-short commodity benchmarks (Panel B). There is a stark contrast in the inferences we can make on the pricing of idiosyncratic volatility using one *versus* another type of benchmark. Consistent with the analysis of Ang *et al.* (2006, 2009)

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weight which is standardized to $w_{i,t}^*$ daily so that $\sum_{i=1}^{N} w_{i,t}^* = 1$. The monthly risk premia is the sum of the log daily returns.

for equities, idiosyncratic volatility is priced cross-sectionally and commands a significantly negative risk premium in commodity futures markets when measured using traditional benchmarks (Panel A). However, in the context of pricing models that factor in the backwardation/contango cycle (Panel B), idiosyncratic volatility is not priced in commodity futures markets. This result indicates that idiosyncratic volatility proxies for a risk that relates to the inexorable backwardation/contango cycle. This result aligns well with the fundamental tenet that idiosyncratic volatility can be diversified away and hence, it is not priced. As Table 3 illustrates, the findings are robust across different specifications for each type of benchmark. The estimated price of idiosyncratic volatility is on average -0.3865 in Panel A and -0.1717 in Panel B, and the discrepancy is statistically significant (*t*-statistic of -9.79).[8]

[Insert Table 3 around here]

As possible explanations of this puzzling negative relationship in equity markets, the literature has suggested that it may be an artefact of neglecting expected idiosyncratic skewness (Boyer *et al.*, 2010), lagged returns (Huang *et al.*, 2010) and firm financial distress (Avramov *et al.*, 2012) as factors explaining the cross-section of returns. Following this lead, we test whether the fundamentals of backwardation and contango still have a role to play in explaining the similar idiosyncratic volatility "puzzle" in commodity futures markets after factoring in the one-month lagged commodity excess return or the expected idiosyncratic skewness in equation (2). Following Szymanowska *et al.* (2014), we consider the liquidity measure of Amihud *et al.* (1997) as another explanatory variable for the cross-section of commodity futures returns. Appendix A gives details on the construction of these variables.

Table 4 shows the estimated price of idiosyncratic volatility obtained from these augmented models. It is noticeable that the results are for the most part robust. After factoring

[8] We also considered a third type of benchmark that includes those (traditional or long-short commodity) factor risk premia that are significant at the 5% level according to the estimation results shown in Table 3; namely, SMB, UMD, HP and Mom. The price of idiosyncratic volatility is insignificant with this benchmark. Detailed results are available from the authors upon request.

in these additional control variables, idiosyncratic volatility is still generally negatively priced at the 5% level or better with respect to the traditional benchmarks (Panel A).

[Insert Table 4 around here]

When the long-short commodity benchmarks are adopted instead, the price of idiosyncratic volatility is almost always undistinguishable from zero at the 5% level (Panel B). Overall, the price of idiosyncratic volatility drops from an average of -0.39 in Table 4, Panel A to -0.18 in Table 4, Panel B. Additionally, we confirm that commodities with lower levels of liquidity and lower expected idiosyncratic skewness tend to earn more (Boyer *et al.*, 2010; Szymanowska *et al.*, 2014). Unlike Huang *et al.* (2010) in the context of equities, we do not identify a one-month return reversal in commodity futures markets.

4.2.Idiosyncratic volatility mimicking portfolios

Table 5 summarizes the performance of idiosyncratic volatility strategies based on traditional benchmarks in Panel A and on long-short commodity benchmarks in Panel B (using the same specifications as in Table 3, for comparison). We report conventional performance statistics for the idiosyncratic volatility portfolios obtained using various ranking periods ($R = 1, 3, 6,$ 12 months) and for the combination of them as an equally-weighted (EW) idiosyncratic volatility portfolio. The significance *t*-statistics shown are based on Newey and West (1987) heteroskedasticity and autocorrelation consistent standard errors.

[Insert Table 5 around here]

The idiosyncratic volatility strategies built upon the traditional benchmarks earn on average 3.94% a year; the vast majority (90%) of these strategies generates individually significantly positive mean excess returns at the 10% significance level or better (Panel A).[9] In

[9] In line with the findings in Ang *et al.* (2009) for international equities, the performance of long-short idiosyncratic volatility portfolios of commodity futures is more largely driven by the underperformance of high idiosyncratic volatility commodities (-5.66% per year) than by the outperformance of low idiosyncratic volatility commodities (2.21% per year).

sharp contrast, the idiosyncratic volatility strategies built upon long-short commodity benchmarks earn on average a substantially smaller 1.18% a year, and none of them generate significantly positive mean excess returns (Panel B). Thus, the use of unsuitable (*i.e.*, traditional) benchmarks exaggerates the profitability of idiosyncratic volatility strategies vis-à-vis the more suitable (long-short) commodity benchmarks by an average return of 2.76% a year which is economically and statistically significant (*t*-statistic of 14.03).

Turning our attention to risk-adjusted performance measures, it is noticeable that the Sharpe ratios of idiosyncratic volatility portfolios based on traditional benchmarks appear also inflated (averaging 0.38 in Panel A) *versus* the counterpart portfolios based instead on long-short commodity benchmarks (averaging 0.12 in Panel B). Table 5 also reports the alpha of the idiosyncratic volatility strategies obtained as the intercept estimate of a regression of one-month holding period returns of the long-short portfolios on the corresponding factor risk premia. The alphas inferred from traditional benchmarks (Panel A) are positive and often significant at the 10% level or better, averaging 3.87% a year. Those obtained with long-short commodity benchmarks (Panel B) are zero statistically in all cases, averaging merely 0.86% a year. The 3% difference in average abnormal returns across panels is statistically significant at the 1% level (*t*-statistic of 16.50). Thus, the alphas confirm that the abnormal performance of idiosyncratic volatility portfolios is exaggerated when traditional benchmarks are used.

Unreported statistics suggest that the return distribution of the long-short idiosyncratic volatility portfolios departs from normality. Bearing this finding in mind, Table 5 reports performance measures that consider moments of the return distribution beyond the first two: modified Sharpe ratio and Omega ratio. Altogether these measures do not alter our main conclusion: the performance of idiosyncratic volatility portfolios is substantially lower when suitable (long-short) commodity benchmarks are used to extract the idiosyncratic volatility signal as shown in Panel B, than when unsuitable (traditional) benchmarks are used instead as shown in Panel A. Results available from the authors demonstrate that the lower performance measures obtained in Panel B stem both from lower returns and higher tail risks.

The contrasting findings revealed in the analyses summarized in Table 5, Panels A (traditional benchmarks) and B (long-short commodity benchmarks) lead us naturally to conclude that adopting an unsuitable asset pricing model will lead to the "illusion" of profitability from selling high idiosyncratic volatility portfolios and buying low idiosyncratic volatility portfolios. Two biases are compounded in the former analysis. First, the volatility signal derived from traditional benchmarks is not truly idiosyncratic because it contains a neglected systematic risk component related to the cycle of backwardation and contango present in commodity futures markets. Second, the alpha is subsequently improperly estimated by resorting to the same (unsuitable) traditional benchmark. The abnormal profits of idiosyncratic volatility strategies for commodity futures vanish when the benchmark for the extraction of the idiosyncratic volatility and performance evaluation is an asset pricing model that factors in the inexorable backwardation/contango cycle. Overall, our findings re-affirm the relevance of adopting an appropriate pricing model in order to make reliable inference.

Table 6 reports a set of additional tests conducted to establish the robustness of the time-series results (shown in Table 5). In these tests, we augment the various benchmarks with alternative risk factors based on expected idiosyncratic skewness, past returns or liquidity levels (Appendix A details the construction of these factors). It turns out that the inclusion of these alternative risk factors does not challenge our main findings. To illustrate, the annualized alphas obtained with the augmented traditional benchmarks stand on average at 3.92% in Panel A; those obtained with the augmented long-short commodity benchmarks average a much lower 1.13% in Panel B. While 85% of the alphas are positive and statistically significant at the 10% level or better in Panel A, none is significant in Panel B.

[Insert Table 6 around here]

5. Conclusions

The commodity pricing literature documents that commodity futures risk premia depend on considerations relating to inventory levels, roll-yields, hedging pressure, past performance, total volatility, skewness or liquidity. This article considers idiosyncratic volatility as another potential signal of expected commodity futures returns. Theoretically, the presence of trading costs and the non-marketability of producers' claims suggest that idiosyncratic volatility should be priced (Hirshleifer, 1988). Empirically, however, the evidence to date is not clear-cut (Bessembinder, 1992; Rouwenhorst and Tang, 2012). A pitfall of the extant empirical studies is that they employ pricing models that fail to recognize the fundamentals of backwardation and contango. This calls for a reassessment of the evidence on the pricing of idiosyncratic volatility using both traditional and long-short commodity pricing models.

Using a similar methodology as that employed by Ang *et al.* (2006, 2009) to analyze the pricing of idiosyncratic volatility in equity markets, we establish that inferences on the relation between idiosyncratic volatility and expected commodity futures returns crucially hinge on the asset pricing model used to measure the idiosyncratic volatility signal. When the asset pricing model fails to recognize the backwardation and contango dynamics, idiosyncratic volatility seemingly commands a puzzling negative risk premium and, relatedly, mimicking portfolios that systematically buy low idiosyncratic volatility commodities and short high idiosyncratic volatility commodities offer sizeable abnormal returns. *Prima facie* these results extend those of Ang *et al.* (2009) from international equity markets to commodity futures markets. However, if the methodology of Ang *et al.* (2009) is instead deployed using suitable benchmarks that incorporate the commodity risk premia related to the backwardation versus contango fundamentals, then idiosyncratic volatility is not priced cross-sectionally and the abnormal performance of long-short idiosyncratic volatility mimicking portfolios vanishes. These conclusions are unchallenged when illiquidity is considered as a risk factor. They are also robust to the inclusion in the various pricing models of "missing" factors such as expected idiosyncratic skewness or past returns that have been shown to rationalize the puzzling negative pricing of idiosyncratic volatility in equity markets.

Finding that idiosyncratic volatility is not priced in the context of suitable benchmarks aligns well with the notion that investors ought not to be rewarded for taking a risk that can be diversified away. Our study shows that the negatively priced idiosyncratic volatility extracted from unsuitable (traditional) benchmarks is an artifact of neglecting the inexorable phases of backwardation and contango of commodity futures markets. As a byproduct, our findings support the recent literature that underscores the information content of backwardation and contango not only as regards the pricing of commodities (Basu and Miffre, 2013; Szymanowska *et al.*, 2014; Bakshi *et al.*, 2015) but also as leading indicator of economic activity (Baker and Routledge, 2012; Bakshi *et al.* 2015; Fernandez-Perez *et al.*, 2015).

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Table 1. Descriptive statistics for the factor risk premia.

The table presents summary statistics for traditional risk premia (Panel A) and long-short commodity risk premia (Panel B) sampled at daily frequency from January 3, 1989 to December 31, 2013. Conventional significance *t*-ratios are reported in parentheses. Sharpe ratios are annualized mean excess returns (Mean) divided by annualized standard deviations (StDev). S&P-GSCI stands for the excess returns of the thus named long-only commodity index, Rm-Rf for the excess value-weighted returns of U.S. CRSP firms, Barclays for the excess returns on the Barclays U.S. Aggregate Bond Index, SMB and HML are the size premium and value premium of Fama and French (1993), UMD is the momentum returns of Carhart (1997), TS, HP and Mom stands for the excess returns of long-short portfolios based on term structure, hedging pressure and momentum signals, respectively.

	Mean		StDev	Sharpe ratio
Panel A: Traditional risk premia				
S&P-GSCI	0.0042	(0.10)	0.2122	0.0198
Rm-Rf	0.0754	(2.07)	0.1783	0.4228
Barclays	0.0373	(4.69)	0.0389	0.9597
SMB	0.0110	(0.60)	0.0894	0.1229
HML	0.0283	(1.52)	0.0908	0.3117
UMD	0.0836	(3.02)	0.1353	0.6179
Panel B: Long-short commodity risk premia				
TS	0.0418	(2.02)	0.1009	0.4140
HP	0.0448	(2.29)	0.0955	0.4694
Mom	0.0601	(2.48)	0.1186	0.5069

Table 2. Correlations among the factor risk premia.

The table reports the pairwise Pearson correlations for all factors risk premia sampled at daily frequency from January 3, 1989 to December 31, 2013. Significance *p*-values are reported in parentheses. S&P-GSCI stands for the excess returns of the thus-named long-only commodity index, Rm-Rf for the excess value-weighted returns of all U.S. CRSP firms, Barclays for the excess returns on the Barclays U.S. Aggregate Bond Index, SMB and HML are the size premium and value premium of Fama and French (1993), UMD is the momentum returns of Carhart (1997), TS, HP and Mom stands for the excess returns of long-short portfolios based on term structure, hedging pressure and momentum signals, respectively.

	Traditional risk premia						Long-short commodity risk premia	
	S&P-GSCI	Rm-Rf	Barclays	SMB	HML	UMD	TS	HP
Rm-Rf	0.139							
	(0.000)							
Barclays	-0.106	-0.077						
	(0.000)	(0.000)						
SMB	0.052	-0.026	-0.124					
	(0.000)	(0.045)	(0.000)					
HML	0.120	-0.163	-0.019	-0.116				
	(0.000)	(0.000)	(0.132)	(0.000)				
UMD	-0.044	-0.231	0.121	0.066	-0.258			
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)			
TS	0.209	0.018	-0.014	-0.017	0.030	-0.014		
	(0.000)	(0.165)	(0.293)	(0.178)	(0.018)	(0.287)		
HP	-0.059	0.008	0.022	0.025	-0.010	0.032	0.210	
	(0.000)	(0.539)	(0.093)	(0.050)	(0.422)	(0.014)	(0.000)	
Mom	0.247	-0.041	-0.009	0.012	0.027	0.122	0.372	0.302
	(0.000)	(0.002)	(0.491)	(0.364)	(0.036)	(0.000)	(0.000)	(0.000)

Table 3. Cross-sectional pricing of idiosyncratic volatility.

The table reports the prices of risk estimates obtained with the two-pass regression approach described in Section 2.1 of the paper. Shanken (1992) adjusted *t*-statistics are reported in parentheses. Bold denotes significance at the 5% or 1% levels. The entry labeled IVol reports the price of idiosyncratic volatility, while S&P-GSCI, Rm-Rf, Barclays, SMB, HML, UMD, TS, HP and Mom refer to the prices of risk associated with the excess returns of the thus-named long-only commodity index, the value-weighted portfolio of U.S. CRSP firms, Barclays U.S. Aggregate Bond Index, size, value and momentum equity portfolios, and long-short commodity portfolios based on term structure, hedging pressure and momentum signals, respectively. The sample period is January 3, 1989 to December 31, 2013.

	Panel A				**Panel B**			
	Traditional benchmarks				**Long-short commodity**			
Model	(A)	(B)	(C)	(D)	(1)	(2)	(3)	(4)
Constant	**0.0050**	**0.0042**	**0.0041**	0.0036	0.0017	0.0016	**0.0026**	0.0023
	(3.36)	(2.72)	(2.40)	(1.95)	(1.03)	(1.00)	(2.03)	(1.55)
IVol	**-0.3829**	**-0.4021**	**-0.4278**	**-0.3331**	-0.1882	-0.1530	-0.1597	-0.1859
	(-3.86)	(-3.75)	(-3.60)	(-2.47)	(-1.45)	(-1.32)	(-1.75)	(-1.76)
S&P-GSCI	0.0012	0.0018	0.0024	0.0011				
	(0.73)	(1.07)	(1.26)	(0.58)				
Rm-Rf		0.0026	0.0023	0.0028				
		(1.34)	(1.02)	(1.16)				
Barclays		-0.0004	-0.0007	-0.0007				
		(-0.81)	(-1.12)	(-1.13)				
SMB			**0.0037**	**0.0039**				
			(3.15)	(3.12)				
HML			0.0012	0.00117				
			(0.95)	(0.90)				
UMD				**-0.0050**				
				(-2.54)				
TS					0.0000			
					(0.06)			
HP					**0.0024**	**0.0022**	**0.0019**	
					(3.41)	(3.13)	(3.32)	
Mom					**0.0020**	0.0016		0.0008
					(2.01)	(1.62)		(0.91)
Adjusted-R^2	12%	21%	27%	31%	23%	18%	11%	13%

Table 4. Robustness of the cross-sectional analysis.

The table reports OLS estimates of the cross-section regression, equation (2), augmented with some alternative factors. Shanken (1992) adjusted *t*-statistics are reported in parentheses. Bold denotes significance at the 5% or 1% levels. Rows labeled IVol, E(*iSK*), $r_{i,t}$ and Liquid report the prices of risk associated with idiosyncratic volatility and additional factors: expected idiosyncratic skewness (Panel I), lagged return (Panel II) and liquidity (Panel III), respectively. Traditional benchmarks (A) to (D) and long-short commodity benchmarks (1) to (4) are as shown in Table 3. The sample period is January 3, 1989 to December 31, 2013.

	Panel A Traditional benchmarks				**Panel B Long-short commodity benchmarks**			
Model	(A)	(B)	(C)	(D)	(1)	(2)	(3)	(4)
Panel I: Boyer et al. (2010)								
IVol	**-0.3525**	**-0.3820**	**-0.3732**	-0.2776	-0.1665	-0.1473	-0.1588	-0.1903
	(-3.34)	(-3.23)	(-2.85)	(-1.93)	(-1.20)	(-1.14)	(-1.30)	(-1.66)
E(*iSK*)	-0.0035	**-0.0066**	-0.0071	-0.0057	**-0.0083**	**-0.0072**	-0.0057	-0.0018
	(-1.29)	(-2.16)	(-1.87)	(-1.45)	(-2.22)	(-2.18)	(-1.85)	(-0.66)
Panel II: Huang et al. (2010)								
IVol	**-0.4082**	**-0.3878**	**-0.4074**	**-0.3323**	-0.2546	-0.1490	-0.1071	-0.1467
	(-4.00)	(-3.37)	(-3.31)	(-2.53)	(-1.90)	(-1.23)	(-0.92)	(-1.37)
$r_{i,t}$	**0.0211**	0.0175	0.0196	0.0199	0.0037	0.0062	0.0176	**0.0217**
	(2.13)	(1.66)	(1.75)	(1.72)	(0.34)	(0.58)	(1.65)	(2.25)
Panel III: Amihud et al. (1997)								
IVol	**-0.4237**	**-0.4452**	**-0.5022**	**-0.3894**	-0.2346	-0.2012	-0.2123	**-0.2339**
	(-4.17)	(-4.03)	(-4.21)	(-2.84)	(-1.75)	(-1.65)	(-1.81)	(-2.13)
Liquid	**-0.0016**	**-0.0015**	**-0.0015**	**-0.0013**	**-0.0013**	**-0.0014**	**-0.0014**	**-0.0014**
	(-3.12)	(-2.74)	(-2.52)	(-2.23)	(-2.51)	(-2.63)	(-2.62)	(-3.04)

Table 5. Performance of long-short idiosyncratic volatility portfolios.

The table reports the mean excess return, Sharpe ratio, alpha, modified Sharpe ratio and Omega ratio of long-short portfolios that exploit idiosyncratic volatility signals. The figures reported in parentheses are robust Newey-West *t*-statistics. Sharpe ratios are calculated as annualized mean excess returns (Mean) divided by annualized standard deviations. The alpha is modelled as the intercept of a regression of the daily idiosyncratic volatility excess returns on the factor risk premia. Unlike the standard Sharpe ratio, the modified Sharpe ratio uses as denominator a modified Value-at-Risk measure that incorporates an adjustment for skewness and excess kurtosis. The Omega ratio is calculated as the ratio of cumulative gains over cumulative losses. Idiosyncratic volatility is defined, and performance is gauged, according to *traditional* risk premia in Panel A and *long-short commodity* risk premia in Panel B. The ranking period (in months) used to model idiosyncratic volatility is denoted *R*, the holding period is one month throughout. S&P-GSCI stands for the excess returns of the thus-named long-only commodity index, Rm-Rf for the excess value-weighted returns of all U.S. CRSP firms, Barclays for the excess returns on the Barclays U.S. Aggregate Bond Index, SMB and HML are the size premium and value premium of Fama and French (1993), UMD is the momentum returns of Carhart (1997), TS, HP and Mom stands for the excess returns of long-short portfolios based on term structure, hedging pressure and momentum signals, respectively. The sample covers the period from February 03, 1989 to December 31, 2013.

Table 5. Performance of long-short idiosyncratic volatility portfolios. (*Cont.*)

	Panel A Traditional benchmarks							Panel B Long-short commodity benchmarks						
Portfolios	Mean		Sharpe ratio	Alpha		Modified Sharpe ratio	Omega ratio	Mean		Sharpe ratio	Alpha		Modified Sharpe ratio	Omega ratio
	(A): S&P-GSCI							**(1) TS, HP, Mom**						
R = 1	0.0432	(2.01)	0.4069	0.0429	(2.01)	0.1260	1.0686	0.0226	(1.12)	0.2309	0.0196	(0.98)	0.0656	1.0389
R = 3	0.0388	(1.78)	0.3684	0.0385	(1.78)	0.1122	1.0615	0.0202	(0.98)	0.2036	0.0165	(0.80)	0.0595	1.0339
R = 6	0.0365	(1.67)	0.3453	0.0361	(1.67)	0.1086	1.0577	0.0172	(0.80)	0.1719	0.0139	(0.65)	0.0413	1.0288
R = 12	0.0440	(2.04)	0.4133	0.0435	(2.05)	0.1327	1.0693	0.0117	(0.55)	0.1150	0.0063	(0.30)	0.0168	1.0193
EW	0.0406	(2.03)	0.4163	0.0402	(2.03)	0.1336	1.0699	0.0179	(0.95)	0.2003	0.0141	(0.75)	0.0462	1.0337
	(B): S&P-GSCI, Rm-Rf, Barclays							**(2) HP, Mom**						
R = 1	0.0404	(1.89)	0.3823	0.0372	(1.76)	0.1181	1.0646	0.0167	(0.81)	0.1650	0.0138	(0.67)	0.0472	1.0277
R = 3	0.0369	(1.68)	0.3495	0.0344	(1.58)	0.1063	1.0583	0.0096	(0.45)	0.0920	0.0058	(0.27)	0.0259	1.0154
R = 6	0.0420	(1.91)	0.3965	0.0413	(1.90)	0.1248	1.0665	0.0153	(0.69)	0.1432	0.0108	(0.49)	0.0226	1.0243
R = 12	0.0398	(1.80)	0.3722	0.0395	(1.81)	0.1195	1.0622	-0.0029	(-0.14)	-0.0279	-0.0075	(-0.35)	-0.0043	0.9953
EW	0.0403	(2.02)	0.4133	0.0382	(1.94)	0.1324	1.0693	0.0097	(0.49)	0.1024	0.0057	(0.29)	0.0218	1.0172
	(C): S&P-GSCI, Rm-Rf, Barclays, SMB, HML							**(3) HP**						
R = 1	0.0425	(1.97)	0.4021	0.0402	(1.86)	0.1243	1.0677	0.0270	(1.22)	0.2503	0.0202	(0.92)	0.0592	1.0428
R = 3	0.0404	(1.85)	0.3838	0.0389	(1.79)	0.1164	1.0642	0.0089	(0.39)	0.0798	0.0006	(0.03)	0.0132	1.0137
R = 6	0.0405	(1.82)	0.3803	0.0405	(1.84)	0.1167	1.0640	0.0182	(0.79)	0.1642	0.0104	(0.46)	0.0277	1.0279
R = 12	0.0399	(1.80)	0.3731	0.0403	(1.84)	0.1194	1.0624	0.0075	(0.33)	0.0679	-0.0007	(-0.03)	0.0114	1.0115
EW	0.0415	(2.08)	0.4267	0.0403	(2.03)	0.1362	1.0717	0.0154	(0.73)	0.1515	0.0076	(0.37)	0.0245	1.0259
	(D): S&P-GSCI, Rm-Rf, Barclays, SMB, HML, UMD							**(4) Mom**						
R = 1	0.0278	(1.30)	0.2640	0.0258	(1.21)	0.0825	1.0437	0.0131	(0.62)	0.1271	0.0159	(0.76)	0.0361	1.0212
R = 3	0.0358	(1.63)	0.3372	0.0358	(1.64)	0.1021	1.0562	0.0038	(0.17)	0.0356	0.0065	(0.29)	0.0101	1.0059
R = 6	0.0400	(1.79)	0.3754	0.0412	(1.86)	0.1155	1.0632	0.0012	(0.05)	0.0115	0.0051	(0.23)	0.0028	1.0019
R = 12	0.0395	(1.78)	0.3689	0.0417	(1.90)	0.1181	1.0616	-0.0013	(-0.06)	-0.0130	0.0007	(0.03)	-0.0039	0.9979
EW	0.0369	(1.84)	0.3779	0.0368	(1.85)	0.1205	1.0632	0.0042	(0.21)	0.0446	0.0070	(0.36)	0.0123	1.0074

Table 6. Robustness of the time-series results

The table reports the annualized alphas modelled as the intercept of a regression of idiosyncratic volatility excess returns on the factor risk premia. It tests the robustness of the time-series results to the inclusion in the pricing equation of long-short portfolios based on expected idiosyncratic skewness (Panel I), lagged return (Panel II) or liquidity (Panel III). Models (A)-(D) and (1)-(4) are as specified in Table 5. The figures reported in parentheses are robust Newey-West *t*-statistics. The ranking period (in months) used to model idiosyncratic volatility is denoted *R*, the holding period is one month throughout. The sample covers the period from February 03, 1989 to December 31, 2013.

Table 6. Robustness of the time-series results. (*Cont.*)

	Panel A: Traditional benchmarks								Panel B: Long-short commodity benchmarks							
Model	(A)		(B)		(C)		(D)		(1)		(2)		(3)		(4)	
Panel I: Boyer et al. (2010)																
R = 1	0.0424	(1.91)	0.0450	(2.04)	0.0424	(1.88)	0.0216	(1.00)	0.0205	(1.03)	0.0119	(0.59)	0.0267	(1.23)	0.0122	(0.58)
R = 3	0.0361	(1.59)	0.0375	(1.64)	0.0405	(1.78)	0.0332	(1.48)	0.0193	(0.94)	0.0051	(0.24)	0.0119	(0.53)	0.0011	(0.05)
R = 6	0.0379	(1.66)	0.0419	(1.83)	0.0397	(1.71)	0.0364	(1.60)	0.0197	(0.94)	0.0155	(0.73)	0.0279	(1.26)	0.0027	(0.12)
R = 12	0.0443	(1.98)	0.0474	(2.09)	0.0450	(1.97)	0.0429	(1.91)	0.0057	(0.28)	-0.0079	(-0.38)	0.0102	(0.48)	-0.0029	(-0.14)
EW	0.0402	(1.93)	0.0429	(2.06)	0.0419	(1.99)	0.0335	(1.64)	0.0163	(0.89)	0.0062	(0.33)	0.0192	(0.96)	0.0033	(0.17)
Panel II: Huang et al. (2010)																
R = 1	0.0431	(2.01)	0.0374	(1.76)	0.0405	(1.88)	0.0258	(1.21)	0.0199	(0.99)	0.0137	(0.67)	0.0201	(0.91)	0.0163	(0.77)
R = 3	0.0392	(1.80)	0.0348	(1.59)	0.0396	(1.82)	0.0364	(1.65)	0.0167	(0.81)	0.0062	(0.29)	0.0010	(0.05)	0.0075	(0.34)
R = 6	0.0366	(1.69)	0.0414	(1.90)	0.0405	(1.84)	0.0413	(1.86)	0.0142	(0.66)	0.0106	(0.48)	0.0102	(0.45)	0.0054	(0.24)
R = 12	0.0441	(2.07)	0.0408	(1.87)	0.0416	(1.90)	0.0431	(1.96)	0.0068	(0.32)	-0.0071	(-0.33)	-0.0008	(-0.03)	0.0008	(0.04)
EW	0.0407	(2.05)	0.0388	(1.96)	0.0409	(2.05)	0.0374	(1.88)	0.0144	(0.77)	0.0059	(0.30)	0.0076	(0.37)	0.0075	(0.38)
Panel III: Amihud et al. (1997)																
R = 1	0.0427	(2.00)	0.0372	(1.76)	0.0401	(1.86)	0.0258	(1.21)	0.0230	(1.19)	0.0182	(0.92)	0.0278	(1.33)	0.0182	(0.90)
R = 3	0.0386	(1.78)	0.0345	(1.59)	0.0390	(1.80)	0.0359	(1.64)	0.0199	(1.01)	0.0105	(0.51)	0.0085	(0.40)	0.0088	(0.42)
R = 6	0.0364	(1.69)	0.0416	(1.91)	0.0407	(1.85)	0.0415	(1.87)	0.0182	(0.89)	0.0167	(0.81)	0.0194	(0.92)	0.0079	(0.38)
R = 12	0.0438	(2.07)	0.0398	(1.83)	0.0406	(1.86)	0.0421	(1.92)	0.0113	(0.57)	-0.0012	(-0.06)	0.0093	(0.45)	0.0035	(0.18)
EW	0.0404	(2.04)	0.0384	(1.95)	0.0405	(2.04)	0.0370	(1.87)	0.0181	(1.02)	0.0110	(0.60)	0.0162	(0.85)	0.0096	(0.52)

Appendix A. Measuring expected idiosyncratic skewness and liquidity

This appendix details the construction of the additional independent variables considered to establish the robustness of the baseline cross-sectional and time-series results.

Idiosyncratic skewness, denoted iSk hereafter, is measured in the spirit of Boyer *et al*. (2010) as the skewness of the residuals from a time-series regression of the commodity futures returns on the risk factors postulated by the (traditional or long-short commodity) benchmark of choice; i.e., the residuals of different specifications of Equation (1).

Expected idiosyncratic skewness, denoted $E_t(iSk_{it+R})$ hereafter, is obtained in a two-stage approach. First, we estimate cross-sectional regressions at the end of each month t

$$iSk_{it} = \beta_{0t} + \beta_{1t} iSk_{it-R} + \beta_{2t} \boldsymbol{Z}_{it-R} + v_{it}$$

where iSk_{it} (iSk_{it-R}) with ranking period R = 1, 3, 6 or 12 months is measured as indicated above using daily data within the months $[t-R; t]$ $([t-2R; t-R])$; $\boldsymbol{Z}_{it-R}$ is a vector of commodity-specific controls that originate in the commodity pricing literature: roll yield, past performance, speculators' hedging pressure and hedgers' hedging pressure averaged over the period $[t-2R; t-R]$. Using the estimated parameters and measures iSk_{it} and Z_{it}, we construct at time t an estimate of each commodity's expected idiosyncratic skewness for the subsequent R months; namely, $E_t(iSk_{it+R}) = \hat{\beta}_{0t} + \hat{\beta}_{1t} iSk_{it} + \hat{\beta}_{2t} Z_{it}$.

Following Szymanowska *et al.* (2014), we measure daily liquidity using the Amihud *et al.* (1997)'s definition as the average ratio of a given contract dollar-volume to the absolute return of that contract; the average is computed over the same R months of daily data used to extract the idiosyncratic volatility signal. The thus-obtained expected idiosyncratic skewness and liquidity measures are included as additional factors in the benchmark, equation (2), so as to re-assess the pricing of idiosyncratic volatility. The results are reported in Table 4.

To test the robustness of the time-series evidence, we form long-short portfolios based on either past one-month return, expected idiosyncratic skewness or Amihud *et al.* (1997) liquidity measure. Following Huang *et al.* (2010), the mimicking portfolio for past one-month return buys (shorts) the commodity with best (worst) past one-month performance. Following Boyer *et al.* (2010), the mimicking portfolio for expected idiosyncratic skewness buys (sells) the quintile with the most negative (positive) value of $E_t(iSk_{it+12})$. Following Szymanowska *et al.* (2014), the liquidity risk premium buys (sells) the most illiquid (liquid) quintile over the past 12 months. All long-short portfolios are held for one month on a fully-collateralized basis. The corresponding excess returns of these sequentially-formed long-short portfolios are included as additional factors in the benchmark of choice to re-assess the risk-adjusted performance of the idiosyncratic volatility portfolios. The results are reported in Table 6.