

# Commodity Futures Returns and Idiosyncratic Volatility

October 2012



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## Abstract

This paper studies the relationship between idiosyncratic volatility and expected returns in commodity futures markets. Measuring idiosyncratic volatility relative to traditional pricing models that fail to account for backwardation and contango leads to the puzzling conclusion that idiosyncratic volatility is negatively priced. In sharp contrast, idiosyncratic volatility is not priced when the fundamental backwardation and contango cycle of commodity futures markets is factored in an appropriate benchmark. Further evidence suggests that the idiosyncratic volatility inferred from traditional benchmarks acts as proxy for the risk associated with contangoed contracts.

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

JEL classification: G13, G14.

This research was supported by funding from INQUIRE UK which we gratefully acknowledge. The article represents the views of the authors and not of INQUIRE UK. We would like to thank Katja Ahoniemi, Giuseppe Bertola, Chris Brooks, Jerry Coakley, Abraham Lioui, George Skiadopoulos, Raman Uppal, seminar participants at EDHEC Business School and Universitat de les Illes Balears, Departament d'Economia de l'Empresa, and conference participants at the 2011 CSDA Conference on Computational and Financial Econometrics, London, and at the 2012 EDHEC-Risk Days Conference, London.

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## 1. Introduction

The link between idiosyncratic volatility and mean returns has been the subject of intense scrutiny in the *equity* markets literature. Theoretical arguments rule out any such link since idiosyncratic volatility can be diversified away and thus should not be priced (Sharpe, 1964) or maintain that the link is positive since agents who hold poorly-diversified portfolios demand incremental returns for bearing idiosyncratic volatility (Merton, 1987; Malkiel and Xu, 2002). The empirical evidence is mixed. A number of studies support the contention that idiosyncratic volatility is not priced (Fama and McBeth, 1973; Bali *et al.*, 2005; Bali and Cakici, 2008; Fink *et al.*, 2012; Huang *et al.*, 2010; Han and Lesmond, 2011) but others report evidence in favor of a positive (Malkiel and Xu, 2002; Goyal and Santa-Clara, 2003; Fu, 2009; Garcia *et al.*, 2011) or an anomalous negative link (Guo and Savickas, 2008; Ang *et al.*, 2006, 2009) between idiosyncratic volatility and average returns in equity markets.<sup>1</sup>

This article studies the relation between idiosyncratic volatility and mean returns in commodity futures markets. The role of idiosyncratic volatility as driver of commodity futures risk premia was first conceptualized by Hirshleifer (1988) in a theoretical model that accounts for trading costs and non-marketability of producers claims. The commodity futures risk premium can then be decomposed into two components: the first one, in the spirit of the CAPM, depends on the co-movement of the futures contract with a broad equity index; the second one depends on the idiosyncratic volatility of the contract and net hedging which is positive when hedgers are net short and negative when they are net long. Bessembinder (1992) validates the predictions of Hirshleifer (1988) by showing that idiosyncratic volatility conditional on net hedging commands a positive risk premium in agricultural commodity and foreign currency markets.

While studying the pricing of idiosyncratic volatility in commodity futures markets, the first thorny issue we face relates to the choice of an appropriate asset pricing model or benchmark upon which to model idiosyncratic volatility. Traditional risk factors from equity and fixed income markets or emanating from the APT have been proven to be unsuccessful for pricing commodity futures contracts (Dusak, 1973; Bodie and Rosansky, 1980; Kolb, 1996; Erb and Harvey, 2006; or, more recently Daskalaki *et al.*, 2012). Commodity-specific risk factors (Carter *et al.*, 1983; Chang, 1985; Bessembinder, 1992; De Roon *et al.*, 2000; Basu and Miffre, 2012; Daskalaki *et al.*, 2012; Gorton *et al.*, 2012) have fared somewhat better, but not unanimously so, inasmuch as they capture the fundamentals of backwardation and contango put forward in the theory of storage of Kaldor (1939) and Working (1948, 1949) and in the hedging pressure hypothesis of Cootner (1960) and Hirshleifer (1988). Given the lack of consensus on a suitable asset pricing model or benchmark for commodity futures, the first objective of this paper is to provide evidence on the ability of various risk factors to explain the cross-sectional variation in commodity futures returns. The second objective is to test, through the various asset pricing models considered, the nature of the relation between idiosyncratic volatility and mean returns both in a cross-sectional framework and in a time-series portfolio formation setting.

The main contribution of our study is to demonstrate empirically that inferences on the relation between lagged idiosyncratic volatility and expected returns in commodity futures markets hinge on the choice of asset pricing model. When the pricing model fails to recognize the fundamentals of backwardation and contango it is shown that: a) idiosyncratic volatility is negatively priced cross-sectionally, and b) a mimicking portfolio that over time buys low idiosyncratic volatility commodities and shorts high idiosyncratic volatility commodities offers sizeable alpha. These results are aligned with those reported by Ang *et al.* (2006, 2009) in international equity markets. In sharp contrast, if the natural propensity of commodity markets to be in backwardation/contango is explicitly factored in the benchmark, idiosyncratic volatility is no longer priced cross-sectionally and the alpha of a portfolio that buys low idiosyncratic volatility commodities and shorts high idiosyncratic volatility commodities becomes insignificant. This outcome agrees with

1 - Differences in the asset pricing model used to extract idiosyncratic volatility, in weighting scheme (equal versus value-weighting), and in methodology (cross-sectional versus time-series analysis) have been put forward as possible explanations for the diverging evidence. Other rationales include discrepancies in data set and time period.

the fundamental tenet of finance theory that idiosyncratic volatility can be diversified away and hence, it is not priced. Further, we show that the seemingly negative premium associated with idiosyncratic volatility when inappropriate asset pricing models are used reflects the pricing of contangoed (rather than backwardated) portfolios, suggesting that idiosyncratic volatility acts, in fact, as a proxy for the systematic risk associated with contangoed assets.

The paper is structured as follows. Section 2 introduces the commodity futures data. Section 3 motivates the pricing models considered both theoretically and empirically. Sections 4 and 5 provide cross-sectional and time-series evidence on the relationship between idiosyncratic volatility and commodity futures returns. Section 6 concludes.

## 2. Commodity Futures Data

The research is based on *daily* settlement prices and volume data for 27 commodity futures from January 2, 1979 to August 31, 2011, from Datastream. The 27 commodities are: 12 agricultural (cocoa, coffee C, corn, cotton n°2, frozen concentrated orange juice, rough rice, oats, 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. We track the futures prices on all nearest and second-nearest contracts in order to work with the most traded contracts; the nearest contract is held up to one month before maturity when the position is rolled over to the second-nearest contract. Excess returns (referred to as "returns" afterwards for expositional ease) are measured as logarithmic price differences.

Our empirical analysis also requires observations on the positions of large traders in commodity futures markets, which are provided weekly by the Commodity Futures Trading Commission (CFTC), from January 1986 to August 2011. Large traders have to report *weekly* to the CFTC whether they are commercial (hedgers) or non commercial (speculators) and whether they are long or short. Their declarations compiled in the Aggregated Commitment of Traders report serve as inputs to calculate two hedging pressure measures. *Speculators'* hedging pressure is calculated as the number of their long positions (i.e., open interests or the amount of outstanding contracts) divided by the total number of positions taken by non-commercial traders over the week. *Hedgers'* hedging pressure is defined in terms of their long positions as a fraction of the total open interests associated with commercial traders over the week. For example, a hedging pressure of 0.2 for hedgers means that 20% of hedgers were long and thus 80% were short over the week, which is (as argued in detail in Section 3.1) a sign of backwardation. A hedging pressure of 0.2 for speculators means that 20% of speculators were long and thus 80% were short over the week, which is (as explained next) an indication of contango. The cross-section size ( $N=27$  commodities) of our sample is, in fact, dictated by data availability from the Aggregated Commitment of Traders report.

## 3. Explaining the Cross-Section of Commodity Futures Returns

This section begins by presenting the theoretical motivation behind the pricing models employed and continues by offering empirical evidence on their plausibility.

### 3.1 Theoretical Underpinning of Systematic Risk Factors

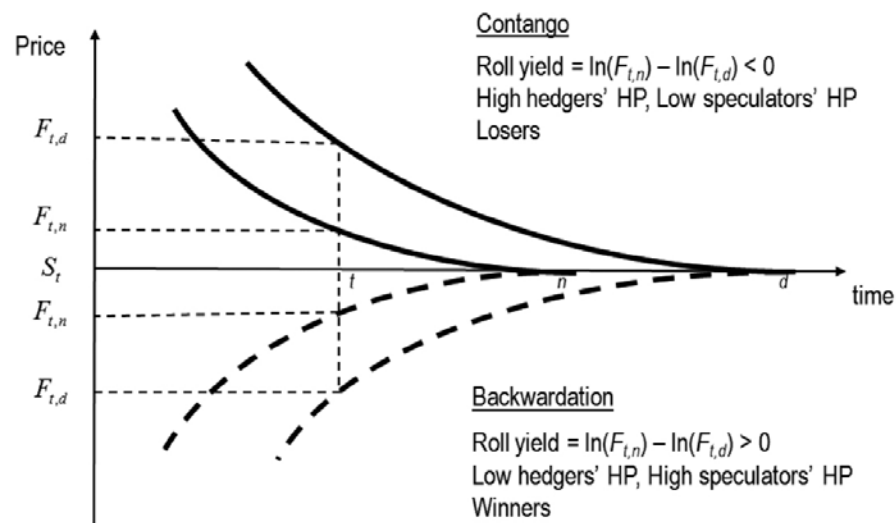
As there is no consensus on the systematic risk factors that should be adopted to model expected commodity futures returns, we measure idiosyncratic volatility relative to several pricing models. This section theoretically motivates the various risk factors. Some of them are borrowed from the literature on the pricing of traditional assets (equities and bonds) under the Law of One Price theory which contends that financial markets are fully integrated (Cochrane, 2005). All other

factors we consider are commodity-specific and are intended to account for the fundamental backwardation/contango cycle of commodity futures.

We use as traditional risk factors: i) the three equity factors of Fama and French (1993), namely, the equity market premium, the size premium (SMB), and the value premium (HML), obtained from Kenneth French's website, and ii) the excess returns of the Barclays US aggregate bond index obtained from *Bloomberg*. The equity market excess return is used as substitute for the true market portfolio assumed by the CAPM. SMB and HML are included as proxies for shifts in the investment opportunity set of agents over time (Petkova, 2006); as such, they could be priced in commodity futures markets too. The inclusion of a fixed income benchmark is motivated by the theory of storage that explains the shape of the commodity futures curve via the cost of borrowing.

The commodity-specific risk factors attempt mainly to capture the fundamentals of backwardation and contango. Broadly speaking, backwardation means that the futures price of a commodity is expected to appreciate as maturity approaches. Contango means the opposite. Figure 1 depicts the theoretical price evolution of two contangoed contracts (continuous lines) and two backwardated contracts (dashed lines) with maturities  $n$  for the nearby contract and  $d$  for the distant contract.

Figure 1. Theoretical price evolution of commodity futures. The figure represents the evolution in the futures prices of two contracts with maturity  $n$  and  $d$  ( $n < d$ ) for a hypothetical commodity when the market is in backwardation (dashed lines) and when it is in contango (continuous lines). Backwardated (contangoed) contracts are characterized by positive roll yield (negative roll yield), low (high) hedgers' hedging pressure (HP), high (low) speculators' hedging pressure and are winners (losers) in a momentum portfolio.  $S_t$  denotes the commodity spot price.



We summon two theoretical rationales to motivate the price evolutions depicted in Figure 1. The first relies on Kaldor's (1939) and Working's (1948, 1949) theory of storage which is empirically supported by Gorton *et al.* (2012). This theory explains the shape of the commodity futures curve by means of the incentive that inventory holders have in owning the commodity spot.<sup>2</sup> Given the difficulty of collecting reliable inventory data, we rely on the slope of the term structure (hereafter TS) of commodity futures prices – instead of standardized inventory levels – as signal for backwardation and contango (Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006; Fuertes *et al.*, 2010; Daskalaki *et al.*, 2012; Gorton *et al.*, 2012). According to the storage theory, as implicitly suggested in Figure 1, we extract the commodity futures risk premium by systematically buying the backwardated contracts with the highest roll yields (or roll returns) and shorting the contangoed contracts with the lowest roll yields.<sup>3</sup>

2 - When inventories are high, commodity futures markets are contangoed – and the term structure of commodity futures prices is upward sloping – giving inventory holders an incentive to buy the commodity spot cheaply and sell it forward at a profit that exceeds the cost of storage and the cost of financing the purchase of the commodity spot. When inventories are low, commodity futures markets are backwardated – and the term structure of commodity futures prices is downward sloping – as the benefits of owning the commodity spot (called convenience yield) then exceed the costs, giving inventory holders an incentive to own the asset spot even though its price exceeds that of the futures contract.

3 - Roll yield equals the differential in the time  $t$  logarithmic prices of the nearby contract that is closed out ( $n$  in Figure 1) and the distant contract that is rolled into ( $d$  in Figure 1).

The second theoretical rationale for the backwardation/contango price evolution depicted in Figure 1 comes from the *hedging pressure* (hereafter HP) hypothesis of Cootner (1960) which is generalized in Hirshleifer (1988) and validated empirically in Bessembinder (1992) and Basu and Miffre (2012). This theory relates backwardation and contango to the propensity of hedgers to be net short or net long.<sup>4</sup> As illustrated in Figure 1, the idea is to capture the risk premium of commodity futures contracts by buying backwardated commodities for which hedgers are the shortest and speculators the longest and by shorting contangoed commodities for which hedgers are the longest and speculators the shortest. To put this differently, the HP mimicking portfolio buys (sells) the commodities for which hedgers' hedging pressure is the lowest (highest) and speculators' hedging pressure is the highest (lowest) following the double-sorting methodology developed in Basu and Miffre (2012).<sup>5</sup>

Our third risk factor is the commodity momentum portfolio (hereafter Mom) advocated by Erb and Harvey (2006) and Miffre and Rallis (2007) that systematically longs commodities with the best past performance and shorts commodities with the worst past performance. While it is not directly intended to do so, this momentum portfolio can also capture to some extent the backwardation/contango cycle. Indeed, Miffre and Rallis (2007) show that the winners (losers) tend to have positive (negative) roll yields making them backwardated (contangoed). However, as illustrated empirically in Fuertes *et al.* (2010), there is no full overlapping of Mom and TS portfolio returns and therefore they can be used in conjunction to model commodity futures risk premia.

Building on the Keynesian hypothesis that commodity futures markets are normally backwardated (Keynes, 1930), we also include as potential risk factor the S&P-GSCI (Standard & Poor's Goldman Sachs Commodity Index) as a long-only commodity market portfolio. Daily data for S&P-GSCI are obtained from *Bloomberg*.

Finally, given that investors demand a premium for holding less liquid assets and in line with the work of Han and Lesmond (2011) that relates the pricing of idiosyncratic volatility to liquidity risk, all our benchmarks include as risk factor the liquidity risk premium (LRP) of Pastor and Stambaugh (2003) that we apply to commodities.<sup>6</sup>

In the remainder of the paper, we adopt the terminology *fundamental commodity benchmarks* to refer to commodity pricing models that account for the fundamentals of backwardation and contango (i.e., those including the TS, HP and/or Mom factors) and *traditional benchmarks* to refer to models that fail to do so (i.e., those based on the Fama-French factors, bond risk premium and S&P-GSCI). The liquidity risk premium is included consistently in all benchmarks of either type.

### 3.2 Empirical Motivation for Fundamental Commodity Benchmarks

This section complements the preceding one by empirically providing some intuition for the TS, HP and Mom factors as drivers of a systematic risk premium in commodity futures markets. Figure 2 plots the evolution from January 1986 to August 2011 of end-of-month futures prices for crude oil. Shaded areas signify backwardated months according to each of three different signals: when the roll yield is positive (TS signal; Panel A), when speculators are net long at the beginning and end of month (HP signal; Panel B), and when 12-month past returns are positive (Mom signal; Panel C). Thus non-shaded areas indicate non-backwardated months when the roll yield is negative (Panel A), speculators are net short at the beginning and end of the month

4 - Backwardation occurs when hedgers are net short (namely, commodity producers are more prone to hedge than commodity consumers and processors), leading to the necessary intervention of net long speculators to restore equilibrium. Contango arises in the opposite case, when hedgers are net long (namely, consumers and processors of a commodity outnumber producers), leading this time around to the necessary intervention of net short speculators.

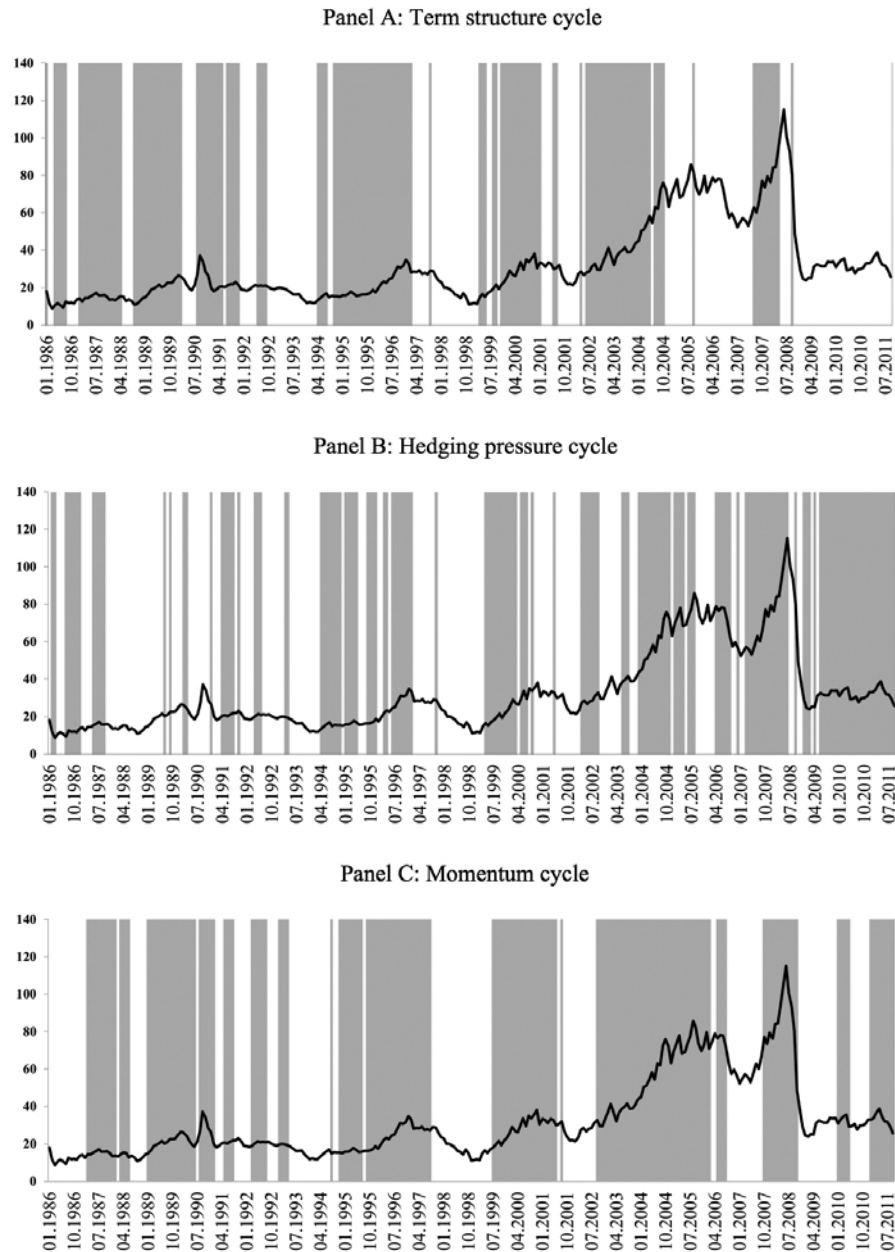
5 - De Roon *et al.* (2000) and Daskalaki *et al.* (2012) propose an alternative (albeit similar in spirit) modeling of the HP risk premium based on the positions of large hedgers only. Instead, Carter *et al.* (1983), Chang (1985) and Bessembinder (1992) use the positions of large speculators only to test the normal backwardation or hedging pressure hypotheses. We combine the positions of both large hedgers and large speculators, following the double-sorting methodology developed in Basu and Miffre (2012), in order to take into account the presence of small traders that represent up to 30% of total open interest. In the absence of small traders the double-sorting becomes redundant as a single-sort hedgers based strategy that takes long (short) positions in the commodities for which hedgers are the shortest (longest) then would generate the same performance as a single-sort speculators based strategy that takes long (short) positions in the commodities for which speculators are the longest (shortest).

6 - In order to construct long-short liquidity risk mimicking portfolios the ranking period is fixed at 60 months, the holding period at 12 months, and each portfolio (long or short) contains 20% of the total cross-section of commodities. Further details on how we applied the methodology of Pastor and Stambaugh (2003) to commodity futures are available upon request.



or changed positions within the month (Panel B), and when 12-month past performance was negative (Panel C). Given that the shaded areas do not strictly coincide in the three panels, we use the TS, HP and Mom factors conjunctly (in pairs or all three) in the benchmarks used to extract and subsequently price idiosyncratic volatility.

Figure 2. Historical crude oil futures prices. The figure plots monthly futures prices of crude oil alongside shaded areas which indicate backwardated months when roll-returns are positive (Panel A), when speculators are net long at the beginning and end of month (Panel B) and when 12-month past returns are positive (Panel C).



The three panels in Figure 2 support the contention that backwardation (grey-shaded area) comes hand-in-hand with upward trends in commodity futures prices. The opposite applies to contango (non-shaded area) which tends to be associated with downward price movements. In order to quantify the evidence presented in Figure 2, we create four dummy variables. One is a return dummy  $D_t^R$  that takes value 1 if the monthly commodity futures return is positive, and 0 if it is zero or negative. The other three dummies are intended to signify months when crude oil is in backwardation:  $D_t^{TS}$  is equal to 1 if the monthly roll-return is positive and 0 otherwise;  $D_t^{HP}$  is set to 1 if speculators are net long at the beginning and end of month and 0 otherwise, and  $D_t^{Mom}$  is set to 1 if the average of 12-month past returns is positive and 0 otherwise. The correlations (and  $p$ -values) between  $D_t^R$  and each of the backwardation dummies,  $D_t^{TS}$ ,  $D_t^{HP}$  and  $D_t^{Mom}$ , equal 30.18% (0.00), 13.68% (0.00) and 11.17% (0.05), respectively. These significantly positive correlations support the notion that TS, HP and Mom are well-suited signals to capture

the fundamental backwardation/contango cycle and thus to model a systematic risk premium inherent in commodity futures markets.

### 3.3 Pricing of Systematic Risk Factors

The following four principles are maintained in constructing the TS, HP and Mom mimicking portfolios that act as proxies for a fundamental commodity risk factor related to the backwardation/contango cycle. First, the long-short portfolios are formed by taking long positions in the 20% most backwardated commodity contracts whose prices are expected to appreciate and short positions in the 20% most contangoed commodity contracts whose prices are expected to decline.<sup>7</sup> Second, the ranking period over which the TS, HP or Mom signals are averaged out is set to 12 months, and the holding period over which the long-short portfolios are being held is set to 1 month.<sup>8</sup> Third, in line with Erb and Harvey (2006) among others, the constituents of the long and short portfolios are equally-weighted.<sup>9</sup> Fourth, the long-short portfolios are fully collateralized, meaning that 1/2 of the trading capital is invested in risk-free interest bearing accounts for the longs and likewise for the shorts. Thus the return of the long-short portfolios equals half the return of the long portfolios minus half the return of the short portfolios.

Our sample comprises daily observations on the three Fama-French risk factors, the commodity futures returns and the (backfilled) S&P-GSCI returns for the period from January 2, 1979 to August 31, 2011. Because the ranking window to construct the long-short TS and Mom mimicking portfolios is set to 12 months, the first set of returns available for them corresponds to January 2, 1980. Since the ranking window for the liquidity risk mimicking portfolio is 60 months, as in Pastor and Stambaugh (2003), the first set of returns for the liquidity risk factor corresponds to January 2, 1985. On the other hand, the availability of hedging pressure data in the Aggregated Commitment of Traders report forces us to start our analysis of the HP risk premium on January 2, 1987. Finally, as the returns on the Barclays bond index are available at a daily frequency from January, 3 1989 onwards, the sample period that is common to all series runs from January 3, 1989 to August 31, 2011.

Table 1 presents pairwise correlations between the daily returns for all risk factors considered over the longest period possible from January 3, 1989 to August 31, 2011. The average absolute correlation is low at 0.08. Unsurprisingly, the highest pairwise correlation of 0.44 corresponds to the two long-short commodity portfolios (Mom and TS), followed by a significant correlation of 0.34 between Mom and HP. Relatively high pairwise correlations among TS, HP and Mom are expected because, arguably, the three factors capture the fundamentals of backwardation and contango. But the fact that these correlations statistically differ from 1 (according to *t*-tests for Pearson correlation) motivates our decision to include two or three of these risk factors simultaneously in the benchmarks; this was also borne out earlier by Figure 2. At the other extreme, the correlation between the equity market factor and HML factor is small at -0.17, and is followed closely by that between HML and SMB also very small at -0.12, as well as between Barclays' bond index and SMB at -0.12 too.

Table 2 reports summary statistics for the daily (annualized or per annum, p.a.) excess returns of the aforementioned risk factors over the period January 3, 1989 to August 31, 2011. Panel A presents the results for the equity and fixed income motivated risk factors whereas Panel B pertains to the commodity-specific risk factors.

7 - Like their TS and Mom counterparts, the long and short HP portfolios contain each 20% of the available cross section. However in the case of the HP portfolio, these 20% commodities stem from a double-sort based on, first, hedgers' HP with the 50th quantile as breakpoint and, second, speculators' HP with the 40th quantile as breakpoint.

8 - The choices of quintiles and of a 12-month ranking and a 1-month holding periods are mainly dictated by Ang et al's (2009) methodology as explained next in the paper. Compared to Daskalaki et al. (2012), our preference for a longer ranking period is also motivated by production cycles and inventory considerations that make it unlikely for futures markets to switch very often between backwardation and contango. Finally, the choice of ranking and holding periods for the Mom factor is in line with the methodology in Gorton et al. (2012).

9 - To obtain the daily returns of the long and short commodity portfolios, we re-balance to equal weights  $w_t = 1/N$  on the 1st trading day of each month and let the weights evolve naturally until the last day of the month,  $w_{i,t} = w_{i,t-1} \cdot (1 + r_{i,t-1})$  where  $r_{i,t}$  is the day *t* return of the *i*<sup>th</sup> commodity and  $w_{i,t}$  is its weight which is standardized to  $w_{i,t}^*$  daily so that  $\sum_{i=1}^N w_{i,t}^* = 1$ .



Table 1. Correlation between daily observations for risk factors from January 3, 1989 to August 31, 2011. The table reports pairwise correlations between risk factors based on daily data from January 3, 1989 to August 31, 2011. Significance p-values are reported in parentheses. SMB and HML are the size premium and value premium of Fama and French (1993), TS, HP and Mom stands for long-short portfolios based on term structure, hedging pressure and momentum signals, respectively, LRP is the liquidity risk premium of Pastor and Stambaugh (2003) applied to commodity futures data.

|               | Equity market   | SMB             | HML             | Bond market     | S&P-GSCI        | TS             | HP             | Mom            | LRP            |
|---------------|-----------------|-----------------|-----------------|-----------------|-----------------|----------------|----------------|----------------|----------------|
| Equity market | 1.00<br>(0.00)  |                 |                 |                 |                 |                |                |                |                |
| SMB           | -0.06<br>(0.00) | 1.00<br>(0.00)  |                 |                 |                 |                |                |                |                |
| HML           | -0.17<br>(0.00) | -0.12<br>(0.00) | 1.00<br>(0.00)  |                 |                 |                |                |                |                |
| Bond market   | -0.06<br>(0.00) | -0.12<br>(0.00) | -0.01<br>(0.42) | 1.00<br>(0.00)  |                 |                |                |                |                |
| S&P-GSCI      | 0.14<br>(0.00)  | 0.03<br>(0.01)  | 0.12<br>(0.00)  | -0.10<br>(0.00) | 1.00<br>(0.00)  |                |                |                |                |
| TS            | 0.02<br>(0.07)  | -0.03<br>(0.06) | 0.03<br>(0.01)  | -0.02<br>(0.11) | 0.26<br>(0.00)  | 1.00<br>(0.00) |                |                |                |
| HP            | 0.00<br>(0.90)  | 0.02<br>(0.09)  | -0.02<br>(0.21) | 0.03<br>(0.03)  | -0.08<br>(0.00) | 0.11<br>(0.00) | 1.00<br>(0.00) |                |                |
| Mom           | -0.03<br>(0.01) | 0.00<br>(0.79)  | 0.01<br>(0.31)  | 0.00<br>(0.86)  | 0.25<br>(0.00)  | 0.44<br>(0.00) | 0.34<br>(0.00) | 1.00<br>(0.00) |                |
| LRP           | 0.01<br>(0.56)  | 0.01<br>(0.54)  | 0.01<br>(0.29)  | 0.01<br>(0.38)  | 0.02<br>(0.06)  | 0.06<br>(0.00) | 0.08<br>(0.00) | 0.09<br>(0.00) | 1.00<br>(0.00) |

Table 2. Summary statistics for risk factors. The table presents in Panel A summary statistics for factors employed in the literature to price traditional assets (equities and bonds). Panel B presents summary statistics for factors that are pertinent to commodity markets as a separate asset class. The observations are daily returns from January 3, 1989 to August 31, 2011. Significance t-ratios are reported in parentheses. The Sharpe ratio is mean excess returns relative to standard deviation.

|  | Mean excess return | Standard deviation | Sharpe ratio |
|--|--------------------|--------------------|--------------|
| <b>Panel A: Traditional risk factors</b>         |                    |                    |              |
| Equity market                                    | 0.0264 (1.81)      | 0.0697             | 0.3795       |
| Size (SMB)                                       | 0.0037 (0.51)      | 0.0348             | 0.1069       |
| Value (HML)                                      | 0.0110 (1.44)      | 0.0362             | 0.3032       |
| Bond market                                      | 0.0360 (4.26)      | 0.0401             | 0.8991       |
| <b>Panel B: Commodity-motivated risk factors</b> |                    |                    |              |
| <u>Long-only portfolio</u>                       |                    |                    |              |
| S&P-GSCI   | 0.0201 (0.44)      | 0.2187             | 0.0920       |
| <u>Long-short portfolios</u>                     |                    |                    |              |
| Term structure (TS)                              | 0.0502 (2.39)      | 0.1017             | 0.4930       |
| Hedging pressure (HP)                            | 0.0563 (3.02)      | 0.0902             | 0.6242       |
| Momentum (Mom)                                   | 0.0766 (3.13)      | 0.1187             | 0.6457       |
| Liquidity (LRP)                                  | 0.0190 (0.90)      | 0.1024             | 0.1859       |

In line with the theoretical argument that the fundamentals of backwardation and contango matter to the pricing of commodity futures contracts, the statistics reported in Panel B provide evidence that the Mom and HP factors, followed by the TS factor, offer the highest Sharpe ratios and thus are more mean-variance efficient than the backwardated-only S&P-GSCI portfolio.<sup>10</sup> Aligned with the notion that long backwardated (contangoed) positions make (lose) money, more detailed analysis reveals that the long TS, HP and Mom portfolios earn positive mean returns of 4.69%, 4.09% and 7.32% p.a., respectively, while the short TS, HP and Mom portfolios earn negative mean returns of -5.34%, -7.17% and -8.00% p.a., respectively.

An appropriate common risk factor should be able to explain the cross-sectional variation in realized commodity futures returns. To gauge this, we follow the two-step approach of Fama and MacBeth (1973) as deployed by Ang *et al.* (2009) to analyze the pricing of idiosyncratic volatility for equities. First, we run time-series regressions for each of the 27 commodity futures, to explain *daily* returns on the basis of  $M$  risk factors

$$r_{i,d} = \alpha_i + \sum_{j=1}^M \beta_{j,i} \cdot f_{j,d} + \varepsilon_{i,d}, \quad d = 1, \dots, D \quad (1)$$

10 - As returns are non-normally distributed, we also compute Omega ratios which confirm that the TS, HP and Mom portfolios outperform the S&P-GSCI.

where  $r_{i,d}$  is the return of the  $i^{\text{th}}$  commodity futures contract on day  $d=1,...,D$  of a given month and  $D$  is the number of days in that month;  $f_{j,d}$  is the  $j^{\text{th}}$  risk factor,  $j=1,...,M$ ;  $\varepsilon_{i,d}$  is an innovation, and  $(\beta_{1,i},..., \beta_{M,i})'$  are the beta parameters of interest. The number of factors,  $M$ , depends on the benchmark at hand. For instance, the first *traditional benchmark* is defined on the basis of the 3 Fama-French factors, Barclays bond index, S&P-GSCI and LRP, thus a total of  $M=6$  factors is used.

Second, we run cross-section regressions of *monthly* commodity returns on the set of step-one monthly betas which can be expressed as follows

$$r_{i,t+1} = \lambda_{0,t+1} + \sum_{j=1}^M \lambda_{j,t+1} \cdot \hat{\beta}_{j,i,t+1} + v_{i,t+1}, \quad i = 1, ..., N \quad (2)$$

where  $r_{i,t+1}$  is the return on the  $i^{\text{th}}$  commodity futures contract in month  $t+1$ ;  $\hat{\beta}_{j,i,t+1}$  are monthly betas estimated by applying OLS to equation (1) on the basis of daily returns within the same month  $t+1$  (i.e., the estimated betas are contemporaneous with the dependent variable); and  $(\lambda_{1,t+1},..., \lambda_{M,t+1})$  are the lambda parameters or prices of risk in month  $t+1$  which are estimated by applying OLS to equation (2). The estimation window for regression (1) is then rolled forward one month, and the resulting betas are used to re-estimate (2) which enables a second set of lambdas and so forth. Shanken's (1992) corrected t-tests are performed on the time-series of lambdas to determine which factors have pricing power for the cross-section of commodity futures returns.

Table 3 reports the averaged lambdas, significance t-tests and adjusted- $R^2$  statistics.

Table 3. Prices of risk factors. The table reports the lambdas of step two cross-sectional regression, equation (2), formulated as in Ang et al. (2009). The step one regression, equation (1), is estimated using daily observations on a given month, and the resulting betas are used to explain cross-sectional returns in the same month. Shanken's (1992) adjusted t-statistics are reported in parentheses. Adjusted- $R^2$  are averages over monthly cross-section regressions, for comparability purposes with all the tables, the first of which corresponds to January 1990. SMB and HML are the size premium and value premium of Fama and French (1993).

|                        | Traditional benchmarks |                    |                    | Fundamental commodity benchmarks |                    |                    |                  |
|------------------------|------------------------|--------------------|--------------------|----------------------------------|--------------------|--------------------|------------------|
|                        | (A)                    | (B)                | (C)                | (D)                              | (E)                | (F)                | (G)              |
| Constant               | -0.0016<br>(-0.87)     | -0.0002<br>(-0.10) | -0.0017<br>(-0.96) | 0.0005<br>(0.28)                 | 0.0009<br>(0.46)   | -0.0001<br>(-0.08) | 0.0004<br>(0.20) |
| Equity risk premium    | -0.0006<br>(-0.36)     | -0.0014<br>(-0.78) |                    |                                  |                    |                    |                  |
| SMB                    | 0.0012<br>(1.32)       | 0.0015<br>(1.56)   |                    |                                  |                    |                    |                  |
| HML                    | 0.0006<br>(0.65)       | 0.0005<br>(0.54)   |                    |                                  |                    |                    |                  |
| Bond risk premium      | 0.0001<br>(0.12)       | 0.0002<br>(0.17)   |                    |                                  |                    |                    |                  |
| S&P-GSCI               | 0.0041<br>(1.06)       |                    | 0.0036<br>(0.96)   |                                  |                    |                    |                  |
| Term structure         |                        |                    |                    | 0.0001<br>(0.04)                 | 0.0006<br>(0.36)   | -0.0001<br>(-0.06) |                  |
| Hedging pressure       |                        |                    |                    | 0.0047<br>(3.33)                 | 0.0043<br>(2.99)   |                    | 0.0045<br>(3.11) |
| Momentum               |                        |                    |                    | 0.0026<br>(1.26)                 |                    | 0.0018<br>(0.88)   | 0.0020<br>(0.97) |
| Liquidity risk premium | 0.0014<br>(0.79)       | 0.0007<br>(0.37)   | 0.0012<br>(0.68)   | -0.0001<br>(-0.03)               | -0.0001<br>(-0.06) | 0.0001<br>(0.03)   | 0.0001<br>(0.04) |
| Adjusted- $R^2$        | 29%                    | 24%                | 15%                | 26%                              | 20%                | 22%                | 22%              |

Notwithstanding the similar explanatory power for the cross-sectional variation in commodity futures returns of all models, the analysis reveals that the HP factor stands out by being able to price the cross-section of commodity futures returns. The largest lambdas in magnitude, strongly significant at the 1% level, are those corresponding to the HP factor in the fundamental commodity benchmarks. This evidence challenges the often-held view that commodities do not constitute another asset class because they do not seem to have a common risk factor (Erb and Harvey, 2006; Daskalaki et al., 2012).<sup>11</sup> The fact that there is at least one commodity-specific risk factor

11 - Two aspects distinguish our HP factor and Daskalaki et al.'s (2012) HP factor. One is that our portfolio construction methodology exploits both *hedgers'* and *speculators'* hedging pressure data (for the reasons given in footnote 5) whereas theirs is solely based on hedgers' hedging pressure. The other is that while they rely on single hedging pressure observations (i.e., hedgers positions available on the last week of month  $t$ ) in order to obtain the long-short HP portfolio return of the subsequent month  $t+1$ , we compute a less noisy HP factor by smoothing (i.e., averaging) the hedging pressure signals over a 12-month ranking period (for the reasons given in footnote 8). The average correlation between the two HP factors is 0.54. Re-estimating the fundamental commodity benchmarks of Table 3 with the HP factor computed as in Daskalaki et al. (2012) leads to findings similar to those reported in their analysis, namely, such HP factor is unable to price the cross-section of commodity futures returns.

that prices commodity futures cross-sectionally indicates that commodities instead constitute a homogeneous alternative asset class. Finding that the sources of risk that explain the cross sectional variations in stocks and bonds returns fail to command a risk premium in commodity futures markets supports, however, the contention that financial markets are segmented.

#### 4. Cross-sectional Pricing of Idiosyncratic Volatility

In this section, we begin by investigating the relationship between commodity futures returns and their past idiosyncratic volatility in a cross-sectional setting.

##### 4.1 Is Idiosyncratic Volatility Priced in Commodity Futures Markets?

Our methodology follows closely Ang *et al.*'s (2009) in their analysis of the relation between future *equity* returns and idiosyncratic volatility. The first stage time-series regression (1) is estimated with daily observations over windows spanning the period from months  $t-R$  to  $t$ , with  $R = \{1, 3, 6, 12\}$  months. This enables sequential idiosyncratic volatility measures for the  $i^{\text{th}}$  commodity,  $\hat{\sigma}_{\varepsilon,i,t}^R$ , computed as the standard deviation of the regression residuals over rolling *ranking* windows of length  $R$ .

In the second stage, we now estimate by OLS the monthly cross-section regressions

$$r_{i,t+1} = \lambda_{0,t+1} + \lambda_{IV,t+1} \cdot \hat{\sigma}_{\varepsilon,i,t}^R + \sum_{j=1}^M \lambda_{j,t+1} \cdot \hat{\beta}_{j,i,t+1} + v_{i,t+1}, \quad i = 1, \dots, N \quad (3)$$

where  $\hat{\beta}_{j,i,t+1}$  is as defined above after equation (2), and  $v_{i,t+1}$  is a random error term. Thus we can estimate lambdas ( $\lambda_{IV,t+1}, \lambda_{1,t+1}, \dots, \lambda_{M,t+1}$ ) or the prices of the  $M+1$  risk factors. This 2-stage procedure is applied iteratively until the sample ends. The significance of the lambdas is then tested using Shanken's (1992) corrected  $t$ -tests.

Because of data availability constraints for Barclays' bond index (only available from January 1989) and given our choice of largest ranking period  $R$  at 12 months to obtain the idiosyncratic volatility in equation (1), the monthly lambdas (prices of risk) summarised in the tables thus far are for months from January 1990 onward. Table 4 reports averages of the lambdas pooled across the different window sizes considered  $R = \{1, 3, 6, 12\}$  months, and the adjusted- $R^2$  averaged across regressions. Given that the size factor (SMB) appears significantly priced at the 1% level in the *traditional benchmarks* shown in Table 4 (i.e., models A and B), we consider as *fundamental commodity benchmarks* those as initially defined (i.e., models D to G) and augmented versions thereof that include the SMB factor (i.e., models H to K).

There is a striking contrast between the results for the *traditional benchmarks*, models A to C, and those for the *fundamental commodity benchmarks*, models D to K. Consistent with the evidence in Ang *et al.* (2009) for equities, idiosyncratic volatility of commodity futures is significantly priced and commands a negative risk premium when modelled relative to *traditional benchmarks*. It is not priced, however, when measured using *fundamental commodity benchmarks*.<sup>12</sup> As suggested by a large  $t$ -statistic equal to  $-3.90$ , the prices of idiosyncratic volatility modelled using *traditional benchmarks* are on average significantly lower than those suggested by *fundamental benchmarks*. These findings suggest that, as long as expected returns accurately reflect the fundamentals of backwardation and contango, idiosyncratic volatility does not appear to be priced which is in line with the finance tenet that idiosyncratic volatility can be diversified away.

12 - As in Ang *et al.* (2009), the betas used as regressors  $\{\hat{\beta}_{j,i,t+1}\}$  and the regressand  $r_{i,t+1}$  are *contemporaneous* in equation (3). We obtained qualitatively similar results when *past* betas  $\{\hat{\beta}_{j,i,t}\}$  are used as regressors instead, that is, slope coefficients of equation (1) estimated on the basis of daily returns in the window from month  $t-R$  to month  $t$ .

Table 4. Cross-sectional pricing of idiosyncratic volatility. The table reports the lambdas of step two cross-sectional regression, equation (3), formulated as in Ang *et al.* (2009). The step one regression, equation (1), is estimated over  $R=\{1, 3, 6, 12\}$  months of daily observations, and the resulting idiosyncratic volatility and contemporaneous betas are used to explain cross-sectional returns in the following month. Shanken's (1992) adjusted t-statistics are reported in parentheses. Adjusted- $R^2$  are averages over monthly cross-section regressions, the first of which corresponds to January 1990. SMB and HML are the size premium and value premium of Fama and French (1993).

|                          | Traditional benchmarks |                    |                    | Fundamental commodity benchmarks |                    |                    |                    |                    |                    |                    |                    |
|--------------------------|------------------------|--------------------|--------------------|----------------------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
|                          | (A)                    | (B)                | (C)                | (D)                              | (E)                | (F)                | (G)                | (H)                | (I)                | (J)                | (K)                |
| Constant                 | 0.0066<br>(3.40)       | 0.0040<br>(2.13)   | 0.0072<br>(3.64)   | 0.0012<br>(0.61)                 | 0.0017<br>(0.85)   | 0.0020<br>(1.03)   | 0.0023<br>(1.29)   | -0.0004<br>(-0.22) | 0.0007<br>(0.37)   | -0.0004<br>(-0.22) | 0.0014<br>(0.79)   |
| Idiosyncratic volatility | -0.6109<br>(-4.40)     | -0.2746<br>(-2.16) | -0.5894<br>(-4.67) | -0.0122<br>(-0.08)               | -0.0548<br>(-0.35) | -0.1284<br>(-0.90) | -0.1183<br>(-0.90) | 0.0192<br>(0.13)   | -0.0412<br>(-0.28) | -0.0317<br>(-0.23) | -0.1228<br>(-0.98) |
| Equity risk premium      | -0.0004<br>(-0.45)     | -0.0019<br>(-2.04) |                    |                                  |                    |                    |                    |                    |                    |                    |                    |
| SMB                      | 0.0013<br>(2.88)       | 0.0017<br>(3.41)   |                    |                                  |                    |                    |                    | 0.0014<br>(2.96)   | 0.0012<br>(2.54)   | 0.0016<br>(3.40)   | 0.0010<br>(2.17)   |
| HML                      | 0.0007<br>(1.37)       | 0.0007<br>(1.43)   |                    |                                  |                    |                    |                    |                    |                    |                    |                    |
| Bond risk premium        | -0.0002<br>(-0.34)     | 0.0000<br>(-0.06)  |                    |                                  |                    |                    |                    |                    |                    |                    |                    |
| S&P-GSCI                 | 0.0034<br>(1.76)       |                    | 0.0026<br>(1.39)   |                                  |                    |                    |                    |                    |                    |                    |                    |
| Term structure           |                        |                    |                    | 0.0001<br>(0.16)                 | 0.0005<br>(0.62)   | 0.0000<br>(0.01)   |                    | 0.0001<br>(0.10)   | 0.0004<br>(0.42)   | 0.0001<br>(0.15)   |                    |
| Hedging pressure         |                        |                    |                    | 0.0045<br>(6.24)                 | 0.0040<br>(5.49)   |                    | 0.0044<br>(6.02)   | 0.0050<br>(7.10)   | 0.0043<br>(5.91)   |                    | 0.0048<br>(6.70)   |
| Momentum                 |                        |                    |                    | 0.0030<br>(2.90)                 |                    | 0.0024<br>(2.36)   | 0.0025<br>(2.39)   | 0.0036<br>(3.53)   |                    | 0.0033<br>(3.21)   | 0.0031<br>(3.00)   |
| Liquidity risk premium   | 0.0016<br>(1.70)       | 0.0004<br>(0.49)   | 0.0012<br>(1.31)   | 0.0000<br>(0.01)                 | 0.0001<br>(0.15)   | 0.0001<br>(0.10)   | 0.0002<br>(0.21)   | 0.0007<br>(0.76)   | 0.0006<br>(0.61)   | 0.0005<br>(0.56)   | 0.0004<br>(0.46)   |
| Adjusted- $R^2$          | 31%                    | 26%                | 18%                | 28%                              | 23%                | 24%                | 24%                | 30%                | 26%                | 27%                | 26%                |

As robustness tests, we estimate three other specifications of the *traditional benchmarks* that replace in models A and C of Table 4 the S&P-GSCI portfolio by either the Thomson Reuters/Jefferies CRB Index, the Dow Jones-UBSCI or a long-only equally-weighted monthly-rebalanced portfolio of all 27 commodities. We also estimate three other re-specifications of the *fundamental commodity benchmarks* labelled D to G in Table 4 that consider either one of the fundamental risk factors (TS, HP or Mom) in isolation instead of considering them as pairs or triplets. Finally, as the equity risk premium is negatively priced in benchmark B of Table 4, we estimate a final set of *fundamental commodity benchmarks* that include both the equity risk premium and SMB in models H to K. None of these robustness checks challenges the earlier evidence presented in Table 4. Unreported results (available upon request) indeed show a negative and significant relationship between idiosyncratic volatility and mean returns in the context of *traditional benchmarks* and an insignificant relationship between idiosyncratic volatility and mean returns in the context of *fundamental benchmarks*.

As a further robustness check, we estimate equation (3) including the one-month lagged returns  $r_{i,t}$  as an additional regressor and the results are shown in Table 5.

The motivation for this analysis stems from Huang *et al.* (2010) who argue that the negative idiosyncratic volatility premium for equities documented by Ang *et al.* (2006, 2009) is induced by a return-reversal omitted variable. The findings suggest that  $\hat{\sigma}_{e,i,t}^R$  is still negatively priced for commodities in the context of *traditional benchmarks* when the lagged return is factored in, and  $\hat{\sigma}_{e,i,t}^R$  is still not priced with *fundamental commodity benchmarks*, consistent with our earlier findings.

Bessembinder (1992) shows that idiosyncratic volatility conditional on net hedging pressure is positively priced in agricultural and foreign exchange futures markets, a result consistent with the theoretical model formulated in Hirshleifer (1988). Following their lead, using our dataset and pricing models (A to K) we investigate whether hedging-conditioned idiosyncratic volatility commands a positive risk premium too.

Table 5. Return reversal. The table reports the lambdas of step two cross-sectional regression, equation (3), as in Ang *et al.* (2009). The step one regression equation (1) is estimated over  $R=\{1,3,6,12\}$  months of daily observations and the resulting idiosyncratic volatility, lagged monthly return and contemporaneous betas are used to explain the cross-sectional returns. Shanken's (1992) adjusted  $t$ -statistics are reported in parentheses. Adjusted- $R^2$  are averages over monthly cross-section regressions, the first of which corresponds to January 1990. SMB and HML are the size premium and value premium of Fama and French (1993).

|                          | Traditional benchmarks |                    |                    | Fundamental commodity benchmarks |                    |                    |                    |                    |                    |                    |                    |
|--------------------------|------------------------|--------------------|--------------------|----------------------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
|                          | (A)                    | (B)                | (C)                | (D)                              | (E)                | (F)                | (G)                | (H)                | (I)                | (J)                | (K)                |
| Constant                 | 0.0064<br>(3.28)       | 0.0034<br>(1.90)   | 0.0065<br>(3.26)   | 0.0014<br>(0.72)                 | 0.0014<br>(0.68)   | 0.0027<br>(1.37)   | 0.0030<br>(1.66)   | 0.0006<br>(0.31)   | 0.0012<br>(0.62)   | 0.0007<br>(0.39)   | 0.0024<br>(1.37)   |
| Idiosyncratic volatility | -0.6088<br>(-4.20)     | -0.3370<br>(-2.54) | -0.5638<br>(-4.28) | -0.0489<br>(-0.33)               | -0.0509<br>(-0.33) | -0.1922<br>(-1.35) | -0.1955<br>(-1.43) | -0.0722<br>(-0.48) | -0.0973<br>(-0.65) | -0.1062<br>(-0.74) | -0.2075<br>(-1.56) |
| Lagged return            | 0.0078<br>(0.70)       | -0.0052<br>(-0.43) | 0.0097<br>(0.83)   | -0.0092<br>(-0.84)               | 0.0040<br>(0.37)   | -0.0093<br>(-0.84) | -0.0092<br>(-0.88) | -0.0028<br>(-0.25) | 0.0050<br>(0.45)   | -0.0102<br>(-0.96) | -0.0102<br>(-0.95) |
| Equity risk premium      | -0.0001<br>(-0.06)     | 0.0001<br>(0.05)   |                    |                                  |                    |                    |                    |                    |                    |                    |                    |
| SMB                      | 0.0014<br>(2.97)       | 0.0007<br>(1.45)   |                    |                                  |                    |                    |                    | 0.0019<br>(3.66)   | 0.0014<br>(3.24)   | 0.0018<br>(3.87)   | 0.0010<br>(2.29)   |
| HML                      | 0.0005<br>(1.05)       | 0.0003<br>(0.52)   |                    |                                  |                    |                    |                    |                    |                    |                    |                    |
| Bond risk premium        | -0.0006<br>(-1.04)     | 0.0006<br>(1.03)   |                    |                                  |                    |                    |                    |                    |                    |                    |                    |
| S&P-GSCI                 | 0.0031<br>(1.65)       |                    | 0.0029<br>(1.57)   |                                  |                    |                    |                    |                    |                    |                    |                    |
| Term structure           |                        |                    |                    | -0.0001<br>(-0.08)               | 0.0004<br>(0.49)   | -0.0006<br>(-0.67) |                    | -0.0001<br>(-0.11) | 0.0003<br>(0.32)   | -0.0004<br>(-0.47) |                    |
| Hedging pressure         |                        |                    |                    | 0.0050<br>(6.68)                 | 0.0047<br>(6.43)   |                    | 0.0051<br>(6.82)   | 0.0055<br>(7.50)   | 0.0049<br>(6.74)   |                    | 0.0055<br>(7.41)   |
| Momentum                 |                        |                    |                    | 0.0041<br>(3.88)                 |                    | 0.0032<br>(3.09)   | 0.0036<br>(3.46)   | 0.0046<br>(4.38)   |                    | 0.0040<br>(3.87)   | 0.0045<br>(4.27)   |
| Liquidity risk premium   | 0.0015<br>(1.55)       | 0.0018<br>(2.00)   | 0.0012<br>(1.30)   | 0.0004<br>(0.44)                 | 0.0003<br>(0.33)   | 0.0006<br>(0.66)   | 0.0003<br>(0.33)   | 0.0007<br>(0.78)   | 0.0001<br>(0.14)   | 0.0007<br>(0.76)   | 0.0004<br>(0.44)   |
| Adjusted- $R^2$          | 34%                    | 26%                | 23%                | 31%                              | 27%                | 28%                | 27%                | 34%                | 30%                | 30%                | 30%                |

This is done by interacting our idiosyncratic volatility measure ( $\hat{\sigma}_{\epsilon,t}^R$ ) with a net hedging pressure dummy that takes value: 1 if speculators are net long at the beginning and end of month (backwardation), -1 if speculators are net short at the beginning and end of month (contango) and 0 if speculators change positions within month. Irrespective of the benchmarks used, we confirm the predictions of Hirshleifer (1988) and the evidence of Bessembinder (1992) of a positive relationship between hedging-conditioned idiosyncratic volatility and mean futures returns. In other words, idiosyncratic volatility commands a positive risk premium in backwardated markets (when speculators are net long) and a negative risk premium in contangoed markets (when speculators are net short). Detailed results are available upon request.

#### 4.2 Is the Idiosyncratic Volatility Puzzle Driven by Backwardation or Contango?

Our main line of reasoning thus far is that the puzzling negative idiosyncratic volatility premium is an artefact of neglecting the fundamental backwardation/contango cycle of commodity futures markets. As Table 4 clearly illustrates, the significantly negative price of idiosyncratic volatility vanishes once backwardation and contango are taken into account through the *fundamental commodity benchmarks*. Out of the two natural states a commodity futures market can be in, it is possible that one of them plays a stronger role to explain the idiosyncratic volatility phenomenon. To gauge this conjecture, we reconduct Ang *et al.*'s (2009) two-stage analysis for the *fundamental commodity benchmarks* but considering this time around the long (backwardated) TS, HP and Mom portfolios, on the one hand, and the short (contangoed) TS, HP and Mom portfolios, on the other. The results are set out in Table 6.

As predicted by the *storage theory* and the *hedging pressure hypothesis*, the prices of risk associated with the long backwardated TS, HP and Mom portfolios are generally positive and significant at the 1% level and the prices of risk associated with the short contangoed TS, HP and Mom portfolios tend to be negative and significant for the most part. This means that investors demand a positive premium (i.e., larger returns) for taking long positions in backwardated assets and short positions in contangoed assets, which is consistent with the price evolution depicted in Figure 1.



Table 6. Backwardation versus contango as explanations for the pricing of idiosyncratic volatility. The table reports the lambdas of step two in Fama-MacBeth's (1973) approach using the fundamental commodity benchmarks listed as D to K in previous tables which are estimated, separately, for long (backwardated) and short (contangoed) mimicking portfolios. Idiosyncratic volatility is measured, separately, with reference to long momentum, term structure and hedging pressure portfolios, on the left-hand side, and short momentum, term structure and hedging pressure portfolios, on the right-hand side. The step one regression (1) is estimated over  $R=\{1, 3, 6, 12\}$  months of daily observations, the resulting idiosyncratic volatility and contemporaneous betas are used to explain cross-sectional returns in the following month. Shanken's (1992) adjusted  $t$ -statistics are reported in parentheses. Adjusted- $R^2$  are averages over monthly cross-section regressions, the first of which corresponds to January 1990.

|                          | Long (backwardated) portfolios |                    |                    |                    |                    |                    |                    |                    | Short (contangoed) portfolios |                    |                    |                    |                    |                    |                    |                    |
|--------------------------|--------------------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|-------------------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
|                          | (D)                            | (E)                | (F)                | (G)                | (H)                | (I)                | (J)                | (K)                | (D)                           | (E)                | (F)                | (G)                | (H)                | (I)                | (J)                | (K)                |
| Constant                 | 0.0027<br>(1.45)               | 0.0021<br>(1.09)   | 0.0046<br>(2.36)   | 0.0020<br>(1.03)   | 0.0020<br>(1.09)   | 0.0014<br>(0.72)   | 0.0027<br>(1.45)   | 0.0021<br>(1.11)   | 0.0010<br>(0.56)              | 0.0023<br>(1.18)   | 0.0000<br>(0.03)   | 0.0029<br>(1.73)   | 0.0000<br>(0.01)   | -0.0013<br>(-0.79) | 0.0006<br>(0.31)   | 0.0014<br>(0.83)   |
| Idiosyncratic volatility | -0.4282<br>(-3.23)             | -0.2599<br>(-1.88) | -0.4651<br>(-3.54) | -0.3214<br>(-2.36) | -0.3942<br>(-2.89) | -0.2390<br>(-1.75) | -0.3754<br>(-2.88) | -0.3538<br>(-2.62) | 0.1327<br>(0.88)              | -0.0513<br>(-0.32) | 0.1789<br>(1.23)   | -0.0358<br>(-0.27) | 0.0460<br>(0.32)   | 0.1596<br>(1.17)   | -0.0511<br>(-0.34) | -0.0029<br>(-0.02) |
| SMB                      |                                |                    |                    |                    | 0.0016<br>(3.46)   | 0.0012<br>(2.67)   | 0.0022<br>(4.69)   | 0.0013<br>(3.04)   |                               |                    |                    |                    | 0.0014<br>(3.07)   | 0.0011<br>(2.38)   | 0.0016<br>(3.41)   | 0.0014<br>(2.84)   |
| Term structure           | 0.0038<br>(2.63)               | 0.0020<br>(1.31)   | 0.0040<br>(2.75)   |                    | 0.0032<br>(2.27)   | 0.0024<br>(1.66)   | 0.0042<br>(2.95)   |                    | 0.0001<br>(0.09)              | 0.0012<br>(0.78)   | 0.0000<br>(-0.02)  |                    | 0.0024<br>(1.52)   | 0.0017<br>(1.13)   | 0.0028<br>(1.82)   |                    |
| Hedging pressure         | 0.0075<br>(5.21)               | 0.0059<br>(4.08)   |                    | 0.0065<br>(4.58)   | 0.0074<br>(5.09)   | 0.0060<br>(4.13)   |                    | 0.0064<br>(4.51)   | -0.0045<br>(-3.29)            | -0.0028<br>(-2.03) |                    | -0.0039<br>(-2.99) | -0.0030<br>(-2.24) | -0.0031<br>(-1.90) |                    | -0.0035<br>(-2.71) |
| Momentum                 | 0.0058<br>(3.43)               |                    | 0.0056<br>(3.31)   | 0.0050<br>(2.89)   | 0.0061<br>(3.61)   |                    | 0.0062<br>(3.68)   | 0.0051<br>(3.00)   | -0.0039<br>(-2.31)            |                    | -0.0037<br>(-2.27) | -0.0024<br>(-1.44) | -0.0021<br>(-1.25) |                    | -0.0018<br>(-1.32) | -0.0021<br>(-1.28) |
| Liquidity risk premium   | 0.0011<br>(1.21)               | 0.0013<br>(1.42)   | 0.0010<br>(1.09)   | 0.0010<br>(1.05)   | 0.0008<br>(0.91)   | 0.0009<br>(1.00)   | 0.0009<br>(0.93)   | 0.0008<br>(0.91)   | 0.0001<br>(0.12)              | 0.0003<br>(0.27)   | 0.0004<br>(0.37)   | 0.0002<br>(0.23)   | 0.0007<br>(0.79)   | 0.0005<br>(0.52)   | 0.0005<br>(0.51)   | 0.0005<br>(0.56)   |
| Adjusted-R <sup>2</sup>  | 27%                            | 23%                | 23%                | 22%                | 29%                | 26%                | 26%                | 25%                | 26%                           | 21%                | 22%                | 21%                | 28%                | 24%                | 24%                | 24%                |

With respect to the idiosyncratic volatility factor, the results for the long backwardated portfolios are very similar to those reported earlier for the *traditional benchmarks* since the premium is significantly negative. For example, while the prices of idiosyncratic volatility inferred from the asset pricing models referred to as *traditional benchmarks* A, B and C in Table 4 stand at -0.4916 on average, the prices of idiosyncratic volatility associated with the long backwardated TS, HP and Mom portfolios in Table 6 average out at -0.3546. In sharp contrast, with an average of only 0.0470, the idiosyncratic volatility premia inferred on the basis of the short contangoed TS, HP and Mom portfolios are economically and statistically undistinguishable from zero.

The most important message stemming from this analysis is that the puzzling negative premium (or discount) that idiosyncratic volatility attracts is an artefact from using an asset pricing model that fails to factor in the risk of contangoed portfolios; once the latter is accounted for, idiosyncratic volatility no longer matters. Thus the earlier finding, on the basis of *traditional commodity benchmarks*, that investors earn a negative premium (i.e., are penalized with a discount) for taking idiosyncratic volatility is spurious since it merely reflects the negative premium (i.e., discount) associated with long positions in contangoed markets. This is quite intuitive because, by being long, investors play the role of hedgers (see Figure 2) and thus pay an insurance premium to short speculators. In other words, by taking long (as opposed to short) positions in contangoed markets, speculators lose the insurance premium they would typically earn.

## 5. Time-Series Pricing of Idiosyncratic Volatility

This section studies the time-series relation between idiosyncratic volatility and returns in commodity futures markets using a risk-mimicking portfolio construction method.

### 5.1 Idiosyncratic Volatility Mimicking Portfolios

Following the analysis in Ang *et al.* (2006, 2009) for equities, we sort commodities into quintiles based on their idiosyncratic volatility  $\sigma_{\epsilon,t,t}^R$ , which is computed using daily returns over the past  $R=\{1,3,6,12\}$  months relative to either *traditional benchmarks* or *fundamental commodity benchmarks*, as in equation (1). We then construct a factor mimicking portfolio that buys the quintile with the lowest idiosyncratic volatility and shorts the quintile with the highest idiosyncratic volatility. We hold the long-short portfolio for one month, at which time the same trading process is repeated to obtain a new long-short idiosyncratic volatility portfolio.



For the sake of consistency with the fundamental risk factors (TS, HP and Mom), the idiosyncratic volatility portfolios are fully-collateralized, rebalanced at the end of each month, and based on equal weights for the constituents of the top and bottom quintiles. While an equal-weighting scheme conveniently avoids portfolio concentration on specific commodities and thus ensures better diversification, it can also cause illiquidity problems, making it potentially difficult for investors to open or close positions. We tackle this issue by including the liquidity risk premium of Pastor and Stambaugh (2003) in all benchmarks.

Table 7 presents summary statistics for the performance of the long-short idiosyncratic volatility portfolios, where idiosyncratic volatility is measured relative to *traditional benchmarks* on the left-hand side, i.e. models A to C, and relative to *fundamental commodity benchmarks* on the right-hand side, i.e. models D to K. An equally-weighted portfolio of all 12 long-short idiosyncratic volatility strategies built upon the *traditional benchmarks* earns 4.94% a year, significant at the 5% level; 10 out of those 12 strategies earn significantly positive mean excess returns at the 10% level (7 out of those 12 mean excess returns are significant at the 5% level or better). In sharp contrast, an equally-weighted portfolio of all 32 long-short idiosyncratic volatility strategies built upon the *fundamental commodity benchmarks* earns about half the above returns, only 2.53% a year, which is statistically insignificant; none of these 32 strategies earn significantly positive mean excess returns. Similar inferences are drawn based on Sharpe ratios, which tend to be much larger (at 0.4543 on average) for *traditional benchmarks* than for *fundamental commodity benchmarks* (at about half, 0.2361 on average); the Opdyke *t*-test statistic equal to 2.30 confirms that the Sharpe ratio of the former is significantly larger than that of the latter.

Table 7. Summary performance of idiosyncratic volatility mimicking portfolios. The table reports the mean excess return, significance *t*-statistic (in parentheses) and Sharpe ratio of long-short portfolios that exploit idiosyncratic volatility signals. *R* stands for the ranking period used to model idiosyncratic volatility, the holding period is one month. Performance is gauged according to the eleven models listed as A to K in the previous tables which are grouped as *fundamental commodity benchmarks*, when the tradable factors included take into account backwardation and contango, and *traditional benchmarks* when they do not. FF stands for the three factors of Fama and French (1993), LRP for the liquidity risk premium obtained a-là Pastor and Stambaugh (2003) using commodity futures data, Bond for Barclays bond index, TS, HP and Mom for long-short portfolios based on term structure, hedging pressure and momentum signals, respectively. Opdyke (2007) *t*-test in the last row is for the significance of differences in the Sharpe ratio of an EW portfolio of *traditional benchmarks* and an EW portfolio of *fundamental commodity benchmarks*.

|                       | Traditional benchmarks         |        |                 | Fundamental commodity benchmarks |        |                 |                               |        |                 |
|-----------------------|--------------------------------|--------|-----------------|----------------------------------|--------|-----------------|-------------------------------|--------|-----------------|
|                       | Mean Excess<br>Return          |        | Sharpe<br>ratio | Mean Excess<br>Return            |        | Sharpe<br>ratio | Mean Excess<br>Return         |        | Sharpe<br>ratio |
|                       | (A) FF + Bond + S&P-GSCI + LRP |        |                 | (D) TS + HP + Mom + LRP          |        |                 | (H) SMB + TS + HP + Mom + LRP |        |                 |
| R = 1                 | 0.0537                         | (2.37) | 0.5100          | 0.0231                           | (1.10) | 0.2374          | 0.0071                        | (0.33) | 0.0719          |
| R = 3                 | 0.0613                         | (2.62) | 0.5646          | 0.0164                           | (0.71) | 0.1539          | 0.0183                        | (0.79) | 0.1697          |
| R = 6                 | 0.0465                         | (1.93) | 0.4162          | 0.0401                           | (1.64) | 0.3526          | 0.0309                        | (1.25) | 0.2697          |
| R = 12                | 0.0539                         | (2.30) | 0.4945          | 0.0338                           | (1.57) | 0.3377          | 0.0322                        | (1.49) | 0.3197          |
|                       | (B) FF + Bond + LRP            |        |                 | (E) TS + HP + LRP                |        |                 | (I) SMB + TS + HP + LRP       |        |                 |
| R = 1                 | 0.0452                         | (1.93) | 0.4151          | 0.0284                           | (1.22) | 0.2627          | 0.0171                        | (0.80) | 0.1713          |
| R = 3                 | 0.0529                         | (2.11) | 0.4542          | 0.0142                           | (0.57) | 0.1231          | 0.0229                        | (0.95) | 0.2053          |
| R = 6                 | 0.0255                         | (1.06) | 0.2287          | 0.0265                           | (1.06) | 0.2283          | 0.0330                        | (1.39) | 0.2991          |
| R = 12                | 0.0312                         | (1.34) | 0.2891          | 0.0257                           | (1.11) | 0.2382          | 0.0260                        | (1.17) | 0.2522          |
|                       | (C) S&P-GSCI + LRP             |        |                 | (F) TS + Mom + LRP               |        |                 | (J) SMB + TS + Mom + LRP      |        |                 |
| R = 1                 | 0.0682                         | (3.04) | 0.6544          | 0.0276                           | (1.26) | 0.2704          | 0.0225                        | (0.94) | 0.2029          |
| R = 3                 | 0.0597                         | (2.58) | 0.5562          | 0.0222                           | (0.94) | 0.2020          | 0.0184                        | (0.74) | 0.1588          |
| R = 6                 | 0.0452                         | (1.90) | 0.4099          | 0.0286                           | (1.21) | 0.2615          | 0.0237                        | (0.94) | 0.2033          |
| R = 12                | 0.0495                         | (2.13) | 0.4583          | 0.0271                           | (1.27) | 0.2739          | 0.0230                        | (0.98) | 0.2118          |
|                       |                                |        |                 | (G) HP + Mom + LRP               |        |                 | (K) SMB + HP + Mom + LRP      |        |                 |
| R = 1                 |                                |        |                 | 0.0245                           | (1.16) | 0.2507          | 0.0205                        | (0.94) | 0.2019          |
| R = 3                 |                                |        |                 | 0.0233                           | (0.98) | 0.2105          | 0.0270                        | (1.14) | 0.2452          |
| R = 6                 |                                |        |                 | 0.0350                           | (1.47) | 0.3159          | 0.0275                        | (1.16) | 0.2489          |
| R = 12                |                                |        |                 | 0.0364                           | (1.63) | 0.3501          | 0.0253                        | (1.18) | 0.2534          |
| EW portfolio          | 0.0494                         | (2.33) | 0.4543          |                                  |        |                 | 0.0253                        | (1.23) | 0.2361          |
| Opdyke <i>t</i> -test |                                |        |                 |                                  |        |                 | (2.30)                        |        |                 |

As in the cross-sectional framework earlier, we test the robustness of our time-series analysis to the specification of the traditional and fundamental commodity benchmarks. This is carried out as follows: i) replacing the S&P-GSCI in models A and C by either the Thomson Reuters/Jefferies CRB Index, the Dow Jones-UBSCI or a long-only equally-weighted portfolio of the 27 commodity

futures, ii) considering either one of the fundamental risk factors (TS, HP or Mom) in isolation instead of treating them as pairs or triplets in models D to G, and iii) including both the equity risk premium and SMB in models H to K. Unreported results indicate that the conclusions of Table 7 hold for these specifications too: as borne out by a significant Opdyke *t*-statistic of 2.59, the average Sharpe ratio of idiosyncratic volatility portfolios based on *traditional benchmarks* (at 0.3895) exceeds that of idiosyncratic volatility portfolios based on *fundamental commodity benchmarks* (at 0.2497).

Table 8 reports annualized abnormal returns or alphas measured as the intercept of a regression of monthly idiosyncratic volatility portfolio returns on various risk factors, alongside significance *t*-statistics based on autocorrelation and heteroskedasticity robust Newey and West (1987) standard errors.<sup>13</sup> Table 8 also presents in the last row a *t*-test for the significance of the difference between two alphas: one corresponding to an equally-weighted portfolio of all 12 idiosyncratic volatility strategies based on traditional benchmarks, the other corresponding to an equally-weighted portfolio of all 32 idiosyncratic volatility strategies based on *fundamental commodity benchmarks*.

Table 8. Abnormal performance of idiosyncratic volatility strategies. The table reports the alpha and Newey-West *t*-statistic (in parentheses) of long-short portfolios that exploit idiosyncratic volatility signals. Identical benchmarks are used to extract the idiosyncratic volatility signal and model alpha. R stands for the ranking period used to model idiosyncratic volatility, the holding period is one month. Performance is gauged according to models which are classified as *fundamental commodity benchmarks*, when the tradable factors included take into account backwardation and contango, and *traditional benchmarks* when they do not. FF stands for the three factors of Fama and French (1993), LRP for the liquidity risk premium a-la Pastor and Stambaugh (2003) using commodity futures data, Bond for Barclays bond index, TS, HP and Mom for long-short portfolios based on term structure, hedging pressure and momentum signals, respectively. The last row reports the alpha of equal-weighted portfolios based on each set of benchmarks and a differential *t*-test (in parentheses).

|         | Traditional benchmarks         |        | Fundamental commodity benchmarks |        |                               |         |
|---------|--------------------------------|--------|----------------------------------|--------|-------------------------------|---------|
|         | (A) FF + Bond + S&P-GSCI + LRP |        | (D) TS + HP + Mom + LRP          |        | (H) SMB + TS + HP + Mom + LRP |         |
| R = 1   | 0.0569                         | (2.74) | 0.0123                           | (0.59) | -0.0005                       | (-0.03) |
| R = 3   | 0.0620                         | (2.62) | 0.0061                           | (0.26) | 0.0159                        | (0.74)  |
| R = 6   | 0.0514                         | (2.13) | 0.0286                           | (1.05) | 0.0235                        | (0.87)  |
| R = 12  | 0.0583                         | (2.57) | 0.0194                           | (0.85) | 0.0207                        | (0.93)  |
|         | (B) FF + Bond + LRP            |        | (E) TS + HP + LRP                |        | (I) SMB + TS + HP + LRP       |         |
| R = 1   | 0.0510                         | (1.99) | 0.0164                           | (0.69) | -0.0016                       | (-0.09) |
| R = 3   | 0.0498                         | (1.77) | 0.0062                           | (0.22) | 0.0176                        | (0.72)  |
| R = 6   | 0.0239                         | (0.92) | 0.0199                           | (0.72) | 0.0325                        | (1.28)  |
| R = 12  | 0.0347                         | (1.27) | 0.0117                           | (0.47) | 0.0204                        | (0.91)  |
|         | (C) S&P-GSCI + LRP             |        | (F) TS + Mom + LRP               |        | (J) SMB + TS + Mom + LRP      |         |
| R = 1   | 0.0706                         | (3.53) | 0.0155                           | (0.68) | 0.0178                        | (0.72)  |
| R = 3   | 0.0642                         | (2.87) | 0.0137                           | (0.54) | 0.0155                        | (0.57)  |
| R = 6   | 0.0510                         | (2.22) | 0.0195                           | (0.76) | 0.0213                        | (0.74)  |
| R = 12  | 0.0511                         | (2.35) | 0.0160                           | (0.74) | 0.0118                        | (0.46)  |
|         |                                |        | (G) HP + Mom + LRP               |        | (K) SMB + HP + Mom + LRP      |         |
| R = 1   |                                |        | 0.0104                           | (0.50) | 0.0296                        | (1.38)  |
| R = 3   |                                |        | 0.0132                           | (0.52) | 0.0380                        | (1.61)  |
| R = 6   |                                |        | 0.0234                           | (0.90) | 0.0331                        | (1.24)  |
| R = 12  |                                |        | 0.0249                           | (1.06) | 0.0210                        | (0.97)  |
| Average | 0.0521                         |        | 0.0179 (8.60)                    |        |                               |         |

The upshot of this analysis is that the inferences on the alpha generation ability of the idiosyncratic volatility portfolios are far more "optimistic" when *traditional benchmarks* are used. In fact, the alphas inferred from *fundamental commodity benchmarks* (i.e., models D to K) are zero statistically whereas those inferred from *traditional benchmarks* (i.e., models A to C) are positive and often significant, averaging 5.21% a year. The empirical evidence that abnormal profits can be made by selling high idiosyncratic volatility portfolios and buying low idiosyncratic volatility portfolios appears to be an artifact of two modeling issues: a) the volatility signal derived from *traditional benchmarks* is not truly idiosyncratic because it contains a systematic risk component related to the neglected fundamental backwardation/ contango cycle and b) the alpha is subsequently gauged using an improper benchmark.

## 5.2 High versus Low Idiosyncratic Volatility Portfolios

In the context of equities, Ang *et al.* (2006, 2009) document that the performance of long-short idiosyncratic volatility portfolios is more strongly driven by the underperformance of stocks with high idiosyncratic volatility than by the outperformance of stocks with low idiosyncratic volatility. To investigate whether the same applies to commodity futures, we measure the alphas of the long idiosyncratic volatility and short idiosyncratic volatility portfolios, separately, where the alphas are calculated relative to either the *traditional* or the *fundamental commodity benchmarks* as defined earlier. Table 9 shows the results.

Table 9. Long versus short idiosyncratic volatility portfolios. The table reports alpha and *t*-ratios, separately, for the long (low) and the short (high) idiosyncratic volatility portfolios. Heteroskedasticity and autocorrelation robust Newey-West *t*-ratios are reported in parentheses. FF stands for the three factors of Fama and French (1993), LRP for the liquidity risk premium à la Pastor and Stambaugh (2003) using commodity futures data, Bond for Barclays bond index, TS, HP and Mom for long-short portfolios based on term structure, hedging pressure and momentum signals, respectively. The last row reports the alpha of equal-weighted portfolios (longs and shorts, in turn) based on each set of benchmarks and *t*-tests in parentheses for the significance of the difference in the average alpha for the two types of benchmarks.

|         | Traditional benchmarks         |         |         |         | Fundamental commodity benchmarks |         |         |         |                               |         |         |         |
|---------|--------------------------------|---------|---------|---------|----------------------------------|---------|---------|---------|-------------------------------|---------|---------|---------|
|         | Long                           |         | Short   |         | Long                             |         | Short   |         | Long                          |         | Short   |         |
|         | (A) FF + Bond + S&P-GSCI + LRP |         |         |         | (D) TS + HP + Mom + LRP          |         |         |         | (H) SMB + TS + HP + Mom + LRP |         |         |         |
| R = 1   | 0.0068                         | (0.57)  | -0.0501 | (-2.72) | -0.0035                          | (-0.21) | -0.0158 | (-0.64) | -0.0099                       | (-0.53) | -0.0094 | (-0.34) |
| R = 3   | 0.0089                         | (0.69)  | -0.0531 | (-2.54) | 0.0102                           | (0.60)  | 0.0041  | (0.16)  | 0.0075                        | (0.41)  | -0.0084 | (-0.33) |
| R = 6   | 0.0151                         | (1.35)  | -0.0363 | (-1.79) | 0.0096                           | (0.59)  | -0.0190 | (-0.66) | 0.0049                        | (0.26)  | -0.0186 | (-0.64) |
| R = 12  | 0.0287                         | (2.24)  | -0.0297 | (-1.48) | -0.0047                          | (-0.30) | -0.0241 | (-0.90) | -0.0077                       | (-0.42) | -0.0284 | (-1.05) |
|         |                                |         |         |         |                                  |         |         |         |                               |         |         |         |
|         | (B) FF + Bond + LRP            |         |         |         | (E) TS + HP + LRP                |         |         |         | (I) SMB + TS + HP + LRP       |         |         |         |
| R = 1   | -0.0063                        | (-0.44) | -0.0572 | (-2.16) | 0.0006                           | (0.04)  | -0.0158 | (-0.63) | -0.0142                       | (-0.83) | -0.0126 | (-0.52) |
| R = 3   | 0.0147                         | (0.94)  | -0.0352 | (-1.29) | 0.0091                           | (0.57)  | 0.0029  | (0.10)  | 0.0084                        | (0.47)  | -0.0092 | (-0.34) |
| R = 6   | 0.0045                         | (0.34)  | -0.0194 | (-0.73) | 0.0130                           | (0.92)  | -0.0069 | (-0.24) | 0.0088                        | (0.57)  | -0.0236 | (-0.84) |
| R = 12  | 0.0055                         | (0.42)  | -0.0292 | (-1.03) | -0.0018                          | (-0.11) | -0.0134 | (-0.49) | -0.0050                       | (-0.31) | -0.0254 | (-0.96) |
|         |                                |         |         |         |                                  |         |         |         |                               |         |         |         |
|         | (C) S&P-GSCI + LRP             |         |         |         | (F) TS + Mom + LRP               |         |         |         | (J) SMB + TS + Mom + LRP      |         |         |         |
| R = 1   | 0.0247                         | (1.17)  | -0.1165 | (-3.27) | 0.0002                           | (0.01)  | -0.0153 | (-0.59) | -0.0012                       | (-0.07) | -0.0190 | (-0.71) |
| R = 3   | 0.0222                         | (1.01)  | -0.1062 | (-2.66) | 0.0125                           | (0.82)  | -0.0013 | (-0.05) | 0.0075                        | (0.41)  | -0.0080 | (-0.28) |
| R = 6   | 0.0381                         | (1.73)  | -0.0638 | (-1.62) | 0.0165                           | (1.00)  | -0.0030 | (-0.11) | 0.0095                        | (0.62)  | -0.0119 | (-0.39) |
| R = 12  | 0.0540                         | (2.53)  | -0.0483 | (-1.26) | -0.0040                          | (-0.24) | -0.0199 | (-0.79) | -0.0067                       | (-0.41) | -0.0184 | (-0.64) |
|         |                                |         |         |         |                                  |         |         |         |                               |         |         |         |
|         |                                |         |         |         | (G) HP + Mom + LRP               |         |         |         | (K) SMB + HP + Mom + LRP      |         |         |         |
| R = 1   |                                |         |         |         | -0.0098                          | (-0.61) | -0.0202 | (-0.76) | -0.0004                       | (-0.02) | -0.0300 | (-1.24) |
| R = 3   |                                |         |         |         | 0.0066                           | (0.42)  | -0.0066 | (-0.24) | 0.0184                        | (1.05)  | -0.0196 | (-0.81) |
| R = 6   |                                |         |         |         | 0.0114                           | (0.80)  | -0.0119 | (-0.43) | 0.0153                        | (0.84)  | -0.0178 | (-0.66) |
| R = 12  |                                |         |         |         | 0.0013                           | (0.08)  | -0.0236 | (-0.89) | -0.0038                       | (-0.21) | -0.0248 | (-0.98) |
|         |                                |         |         |         |                                  |         |         |         |                               |         |         |         |
| Average | 0.0181                         |         | -0.0537 |         |                                  |         |         |         | 0.0031                        | (2.99)  | -0.0148 | (-4.43) |

The results using *traditional benchmarks* are in line with Ang *et al.* (2006, 2009): while the portfolios with low idiosyncratic volatility tend to marginally outperform (with an average alpha at 1.81% a year) the portfolios with high idiosyncratic volatility have very low annualized alphas (at -5.37% on average). Interestingly, when the fundamental backwardation/contango cycle is properly factored in the benchmarks, which are used both to model idiosyncratic volatility and measure abnormal performance, the alphas of the long and short portfolios decrease in absolute value. The last row of Table 9 reports in parenthesis *t*-tests for the significance of the difference in the average alphas (longs and shorts, in turn) for the two types of benchmarks. With *t*-statistics at 2.99 (-4.43), the alphas of the long (short) portfolios for the *traditional benchmarks* denoted A to C are found to be statistically larger (smaller) than the alphas of the long (short) portfolios for the *fundamental commodity benchmarks* denoted D to K. This further substantiates our conjecture that idiosyncratic volatility signals built upon *traditional benchmarks* are partly systematic because they reflect the risk associated with the backwardation/contango cycle. Once the latter is taken into account, the alphas of the long and short idiosyncratic volatility mimicking portfolios become negligible.

## 6. Conclusions

This paper investigates the relation between idiosyncratic volatility and expected returns in commodity futures markets. The analysis is motivated by the puzzling empirical evidence for international equity markets provided by Ang *et al.* (2009) suggesting that idiosyncratic volatility is negatively priced. Extending their analysis to commodity futures markets is of interest not only because it could prove that the puzzling negative relationship is a pervasive phenomenon, but also because it could shed light on the reasons as to why this anomalous effect is revealed by the data. The empirical evidence presented suggests that inferences on the relation between idiosyncratic volatility and expected commodity futures returns depend on the choice of asset pricing model or benchmark used to extract the idiosyncratic volatility signal. When the asset pricing model fails to recognize the inexorable backwardation/contango cycle of commodity futures markets, 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 seem to offer sizeable mean returns. *Prima facie* these results extend those of Ang *et al.* (2009) from international equity markets to commodity futures markets.

However, should commodity futures be priced instead with reference to the fundamentals of backwardation and contango, the abnormal performance of long-short idiosyncratic volatility mimicking portfolios fades away and idiosyncratic volatility no longer commands a negative risk premium. These results align well with the fundamental tenet that idiosyncratic volatility should be diversified away and thus it is not priced. Further evidence shows that the seemingly negative premium associated with idiosyncratic volatility when traditional benchmarks are used is a manifestation of the pricing of contangoed, rather than backwardated, portfolios: idiosyncratic volatility acts as proxy for the risk associated with contangoed contracts.

Further research could extend this analysis to the FOREX futures market where backwardation and contango have been shown to matter (Bessembinder, 1992).

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