IDIOSYNCRATIC VOLATILITY STRATEGIES IN COMMODITY FUTURES MARKETS

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Abstract

This paper studies the relationship between lagged idiosyncratic volatility and subsequent returns in commodity futures markets. The negative pattern observed in international equity markets by Ang et al. (2006, 2009) prevails in commodity futures markets too, suggesting that it may relate to a yet-to-be-specified risk factor that is pervasive across markets. Systematically buying commodities with low idiosyncratic volatility and shorting commodities with high idiosyncratic volatility generates an average alpha of 4.62% a year. Idiosyncratic volatility signals appear more robust to extreme market volatility conditions than momentum and/or term structure signals. Robustness tests show that the profitability of idiosyncratic volatility signals is not an artifact of transaction costs, illiquidity or data mining. They are neither a mere compensation for backwardation and contango nor a manifestation of overreaction.

Keywords: Lagged idiosyncratic volatility; Commodity futures; Backwardation; Contango, Liquidity.

JEL classification: G13, G14.

1. Introduction

An increasing literature documents that commodity futures contracts are attractive candidates for tactical asset allocation. For example, Erb and Harvey (2006) and Miffre and Rallis (2007) show that trading on momentum is a reliable source of alpha in commodity futures markets. More recently, Szakmary et al. (2010) show that pure trend-following strategies (e.g. dual moving average crossover) in commodity futures markets are substantially profitable. Similarly, Erb and Harvey (2006) and Gorton and Rouwenhorst (2006) demonstrate that the term structure of commodity futures prices is a profitable indicator for sorting commodities into portfolios. Jointly exploiting momentum and term structure also materializes in sizeable alphas (Fuertes et al., 2010).

Another strand of the finance literature examines the link between idiosyncratic volatility and equity returns. Theory argues that there is no such a relationship (idiosyncratic volatility is diversified away and thus not priced; Sharpe, 1964) or it is positive (agents who hold undiversified portfolios demand incremental returns for bearing idiosyncratic risk; Merton, 1987; Malkiel and Xu, 2002). At an empirical level, the evidence is quite mixed. While early studies mainly support the notion that idiosyncratic volatility is not priced (e.g., Fama and McBeth, 1973), recent findings support the presence of a positive (Malkiel and Xu, 2002; Goyal and Santa-Clara, 2003; Fu, 2009), negative (Ang et al., 2006, 2009) and zero relationship (Bali et al. 2005; Bali and Cakici 2008; Fink et al., 2010; Huang et al., 2010; Han and Lesmond, 2011) between idiosyncratic volatility and mean returns in equity markets.[1]

Some rationales have been put forward in the commodity futures literature to explain a non-zero relationship between idiosyncratic volatility and returns. Hirshleifer (1988) presents a theoretical framework in which idiosyncratic volatility is priced because of high fixed set-up costs deterring some investors from participating in commodity futures markets. Bessembinder (1992) validates the predictions of Hirshleifer (1988) by showing that the expected return of agricultural commodity futures contracts depends upon idiosyncratic volatility conditioned on net hedging.

[1] Differences in methodology and data frequency to model idiosyncratic volatility, samples, and weighting schemes have been put forward as explanations for the diverging evidence. Others relate to bid-ask bounce (Han and Lesmond, 2011) and return reversals (Huang et al., 2010).

The first purpose of this paper is to empirically assess the relationship between idiosyncratic volatility and mean returns in commodity futures markets. The design of an active commodity strategy based on the relationship uncovered is also of interest to professional money managers such as CTAs, CPOs and hedge funds. The second objective of the paper is to investigate the degree of overlap between idiosyncratic volatility signals and the signals exploited in well-established strategies in commodity markets. Relatedly, we test whether further abnormal returns can be earned by overlaying *idiosyncratic volatility* signals to the hybrid strategy advocated by Fuertes et al. (2010) that jointly exploits *momentum* and *term structure* information. Finally, the third purpose of the paper is to test whether the performance of the then-identified idiosyncratic volatility strategies is robust to a range of issues such as overreaction, backwardation versus contango, illiquidity and data mining. We also assess whether the results withstand reasonable transaction costs and hold in turmoil and tranquil markets.

We draw three key conclusions. First, over the period 1992-2011, commodity futures with low idiosyncratic volatility outperform their high-idiosyncratic volatility counterparts by an average alpha of 4.62% a year; this differential alpha is economically and statistically significant. This serves to extend the evidence of Ang et al. (2006, 2009) from equities to commodity futures markets and hints that the explanation for the observed profitability of idiosyncratic volatility strategies may lie in a yet-to-be-specified macroeconomic or financial factor that is common to both equity and commodity futures markets. Second, the idiosyncratic volatility strategies are shown to have very little overlap with momentum and/or term structure strategies that are also profitable in commodity futures markets. Overlaying the hybrid momentum-term structure strategy advocated in Fuertes et al. (2010) to our idiosyncratic volatility strategy results in a triple-sort strategy that yields average annualized alphas of 5.6%. However, the triple-sort strategies lose out compared to the single-sort idiosyncratic volatility portfolios during extreme high/low market volatility conditions. Third, the profitability of idiosyncratic volatility signals remain unchallenged after introducing reasonable levels of transaction costs and cannot be attributed to overreaction, illiquidity risk, data mining or a mere compensation for backwardation and contango.

The rest of the paper unfolds as follows. Section 2 presents the dataset and explains the design of mean-variance efficient commodity futures benchmarks which is of paramount importance for the appropriate modeling of idiosyncratic volatility. Section 3 uses both a cross-section regression approach and a time-series portfolio formation methodology to analyze the link between lagged idiosyncratic volatility and subsequent commodity futures returns. Section 4 is devoted to the hybrid triple-sort strategy that exploits idiosyncratic volatility, momentum and term structure signals. Section 5 offers various robustness checks before concluding in Section 6.

2. Data and Hedging Pressure Benchmarks

2.1 Commodity Futures Prices and Hedging Pressure

The analysis is based on the Friday settlement prices of 27 commodity futures which are obtained from *Datastream* alongside weekly hedging pressure data from the CFTC Commitment of Traders Report from September 30, 1992 to March 25, 2011. The cross-section, time span and weekly frequency of our sample are determined by the availability of hedging pressure observations; the positions of hedgers and speculators are reported every Friday. The latter are needed for the modeling of the risk premium inherent in the commodity futures market as explained below in the next section. The commodities are: 12 agricultural (cocoa, coffee C, corn, cotton n°2, oats, frozen concentrated orange juice, rough rice, soybean meal, soybean oil, soybeans, sugar n° 11, wheat), 4 energy (electricity, 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), milk and random length lumber.

We collect the futures prices on all nearest and second-nearest contracts. The first nearby contract is held up to one month before maturity when the position is rolled over to the second-nearest contract. Thus positioning the empirical analysis on the front-end of the term structure ensures that we often work with the most traded contracts available. As usual returns are measured as logarithmic price differences.[2]

[2] Our commodity strategies are fully collateralized meaning that half of the trading capital is invested in risk-free interest bearing accounts for the long portfolio and likewise for the short portfolio. Thus investors earn half of the returns of the 'longs' and half of the returns of the

2.2 Efficient Commodity Futures Benchmarks

The idiosyncratic volatility of a stock can be straightforwardly measured as the standard deviation of the residuals from the 3-factor model of Fama and French (1993) or the 4-factor model of Carhart (1997). Unfortunately, these benchmarks cannot be readily applied to commodities in order to measure idiosyncratic volatility for several reasons. First, commodities have been shown to behave differently from stocks and bonds (Erb and Harvey, 2006), making equity and fixed income benchmarks poorly suited to measure the abnormal returns of commodity futures portfolios. Second, there are also grounds to believe that traditional commodity indices such as S&P-GSCI and DJ-UBSCI are sub-optimal benchmarks; their grievances come from their long-only nature, their infrequent rebalancing and their failure to recognize the natural propensity of commodity futures to be either in backwardation or in contango.[3]

In a recent paper, Basu and Miffre (2011) construct a systematic hedging-pressure risk factor that acknowledges the well-accepted tendency of commodity markets to be either in backwardation (i.e., hedgers are net short and speculators are net long) or in contango (i.e., hedgers are net long and speculators are net short). This factor provides a benchmark to extract *abnormal* commodity futures returns that is well-grounded theoretically as it is inspired on the hedging pressure hypothesis of Cootner (1960). Cross-sectional and time-series tests in Basu and Miffre (2011) suggest that the price of commodity risk based on hedging pressure is positive and often significant while the price of risk stemming from the S&P-GSCI is economically and statistically zero.

'shorts'. For expositional simplicity, the empirical results presented hereafter are based on the excess returns, i.e. the total return minus the collateral return. Should the risk-free rate be proxied by the 3-month US Treasury bill rate, the mean return of the collateral over the period considered in the paper would stand at 3.27%. Thus, assuming no margin calls, the gross performance of the unlevered portfolios reported hereafter is understated by that amount.

[3] Backwardation occurs when commodity producers are more prone to hedge than commodity consumers. Their short positions in commodity futures markets create an imbalance between supply and demand that is restored by the intervention of long speculators. Speculators in turn will only go long if the futures price is expected to rise as maturity approaches. In contangoed markets commodity consumers outnumber commodity producers, leading to excess demand for hedging and thus to the essential intervention of short speculators. Speculators will go short if the futures price is expected to fall with maturity. It follows from the fundamentals of commodity futures pricing that, in order to earn a positive risk premium, investors should take long positions in backwardated markets and short positions in contangoed markets.

Large traders have to report to the CFTC whether they are commercial (hedgers) or non commercial (speculators) and whether they are long or short. We use their declarations compiled in the Commitment of Traders report to calculate two hedging pressure measures, one for hedgers and another one for speculators. Speculators' hedging pressure is calculated as the number of *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. Similarly, 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 over the week 20% of hedgers were long and thus 80% were short, a sign of backwardation. A hedging pressure of 0.2 for speculators means that over the week 20% of speculators were long and thus 80% were short, a sign of a contangoed market.

The hedging-pressure mimicking portfolios put forward by Basu and Miffre (2011) are based on a double-sort strategy that combines the positions of hedgers and speculators. First, the cross-section of commodities is split in two halves (using a 50% threshold) on the basis of the average hedging pressure of hedgers over the previous R weeks. The first portfolio, called Low_{Hedg}, contains low hedgers' hedging pressure (backwardated) commodities whose prices are expected to rise. The second portfolio, called $High_{Hedg}$, contains high hedgers' hedging pressure (contangoed) commodities whose prices are expected to fall. Next, the hedger-based signal is combined with a speculator-based signal as follows: out of the constituents of Low_{Hedg}, we buy the 40% with the highest speculators' hedging pressure over the previous R weeks. Similarly, out of the constituents of $High_{Hedg}$, we sell the 40% that have the lowest speculators' hedging pressure over the previous R weeks. This long-short double-sort portfolio is held over H weeks at the end of which the process is repeated. The returns thus obtained represent the hedging-pressure (HP) risk premium that can be cast as a systematic commodity risk factor and, in turn, as a natural benchmark to extract idiosyncratic volatility levels.

Table 1 summarizes the HP risk premium based on the positions of, first, hedgers and, second, speculators, with R, H={4, 13, 26, 52} weeks over the period 1992-2011.

[Insert Table 1 around here]

The superiority of the HP benchmark in terms of mean-variance efficiency is reflected in an average Sharpe ratio that more than doubles that of the S&P-GSCI portfolio and is

9 times higher than the Sharpe ratio of the long-only equally-weighted portfolio of all commodities.[4] Long-only commodity portfolios make inadequate benchmarks to measure idiosyncratic volatility because of their failure to acknowledge the natural propensity of commodities to switch between contango and backwardation.

3. Idiosyncratic Volatility and the Cross Section of Commodity Returns

This section studies the relationship between lagged idiosyncratic volatility and subsequent commodity futures returns using both a cross-section approach (Section 3.1) and a time-series approach (Section 3.2). As explained below, an advantage of the cross-sectional test is that it exploits the entire set of commodity futures contracts and thus retains more power than the time-series test. On the other hand, the cross-sectional approach suffers from the drawback of being less practical relative to time-series tests that enable easy-to-deploy portfolios. For completeness, we present both tests.

3.1 Cross-Sectional Tests

Our methodology builds on Ang et al. (2006, 2009) where the idiosyncratic volatility of equities is modeled as the standard deviation of the residuals from a regression of daily stock returns on the 3-factor model of Fama and French (1993) over the previous month. In the present setting, we formulate instead the following regression model

$$r_{i,t} = \alpha_i + \beta_i . HP_t^{(R,H)} + \varepsilon_{i,t} \quad (1)$$

where $r_{i,t}$ is the return of the i^{th} commodity on week t, $HP_t^{(R,H)}$ is the weekly hedging pressure risk premium obtained as detailed in Section 2, α_i and β_i are parameters to estimate, and $\varepsilon_{i,t}$ is a random error term. For each of the i=1,…, N commodities in the sample, equation (1) is, first, estimated over a 52-week window. Idiosyncratic volatility for the i^{th} commodity over this window, denoted $\sigma_{\varepsilon,i}^{(R,H)}$, is measured as the standard deviation of the residuals. The superscripts R and H refer to the specific ranking and holding periods of the hedging pressure benchmark used as systematic risk factor.

[4] The mean returns of the HP benchmark are statistically larger than those of the traditional long-only benchmarks according to t-statistic based on pooled returns across all the R-H combinations at 2.743(S&P-GSCI) and 6.509 (equal-weighted portfolio).

Sequential weekly cross-section regressions are then estimated to examine the sign of the relation between idiosyncratic volatility and subsequent commodity futures return while taking into account other observable control variables. One such variable is the open interest (OI) or the number of outstanding futures contracts at a given time; large OI indicates more liquidity and increasing OI means that new money is flowing into the marketplace. Following Huang et al. (2010) analysis for equities, we also include past returns as regressor to account for a potential negative bias in the cross-section relationship between returns and lagged idiosyncratic volatility. Huang et al. (2010) illustrate an omitted variable bias problem in monthly cross-section regressions, namely, the combination of monthly return reversals that manifest as negative first-order correlation together with positive cross-section correlation between realized idiosyncratic volatility and returns on the same month. In the first holding period, we estimate H weekly cross-section regressions

$$r_{i,t+j} = \lambda_{0,t} + \lambda_{1,t}\sigma_{\varepsilon,i}^{(R,H)} + \lambda_{2,t}OI_{i,t} + \lambda_{3,t}r_{i,t} + \lambda_{4,t}\beta_i + \upsilon_{i,t+j}, \quad (2)$$

where the subscript $t+j$ with $j = 1,\ldots,H$ represents weeks ranging from 52+1 up to week 52+H; $\sigma_{\varepsilon,i}^{(R,H)}$ and β_i had been obtained by OLS from equation (1) using information up to week 52, $OI_{i,t}$ denotes the logarithmic open interest on week 52, $r_{i,t}$ denotes the past return on week, and $\upsilon_{i,t+j}$ is a random error term. This enables a first sequence of weekly estimates for the parameter vector $\{\lambda_{0,t}, \lambda_{1,t}, \lambda_{2,t}, \lambda_{3,t}, \lambda_{4,t}\}_{t=1}^{H}$.

In a recursive process, the idiosyncratic volatility of each of the N commodity futures is estimated over a second window that comprises 52+H weeks[5], past open interests and returns are measured again over the last week of the window also denoted t. These four new variables, $\sigma_{\varepsilon,i}^{(R,H)}$, $OI_{i,t}$, $r_{i,t}$ and β_i are then used in (2) to explain the H weekly returns in the second holding period, i.e. returns on weeks (52+H)+j, j=1,…,H, which

[5] A recursive window approach is adopted to obtain $\sigma_{\varepsilon,i}^{(R,H)}$ seeking to mitigate estimation noise. Effectively, this approach implies that the cross-section regression (2) estimated each week $t+j$ in the holding period uses as regressor the idiosyncratic volatility signal based on as many weeks of information as possible up to time t. Since the hedging pressure benchmark is obtained using a ranking period of R weeks, the initial estimation window for model (1) to obtain $\sigma_{\varepsilon,i}^{(R,H)}$ necessarily starts R weeks after the start of our on September 30, 1992. This recursive window approach has the advantage over using daily data to estimate (1) month by month of providing by construction a link between adjacent volatilities. As argued by Fink et al. (2010), the latter is important given that strong autocorrelation is a stylized fact of volatility.

enables *H* new parameter estimates. This process is iterated until the end of the sample. We re-formulate regression using as liquidity control the average of logarithmic OI over the ranking weeks immediately preceding portfolio formation (i.e., weeks *t*-*R* to *t*) instead of the logarithmic OI on week *t* as in the original formulation. The cross-section regression estimates are shown in Table 2 as averages over R-H combinations and weekly periods with significance *t*-statistics.

[Insert Table 2 around here]

The mean effect of past idiosyncratic volatility on future returns (λ_1) is uniformly negative and significant. The coefficient λ_3 is insignificant and thus it is not surprising that the inclusion or exclusion of past returns has a negligible impact on the coefficient λ_1. Indirectly, these results point towards the absence of reversals in weekly commodity returns which corroborated by testing for the significance of the first four autocorrelations using the Ljung-Box Q test. The general finding is one of insignificance, for instance, only for 4 out of 27 commodities the first order autocorrelation is significantly negative, in all other cases it is statistically zero, and averages at -0.014 (Q-test *p*-value=0.4294) across commodities. Moreover, there is very little correlation between the regressors $\sigma_{\varepsilon,i}^{(R,H)}$ and $r_{i,t}$ further ruling out reversals (omitted variable bias) as the driver of the negative relation between commodity returns and past idiosyncratic volatility levels. Only the coefficient on open interests measured as an average is significant at the 5% level, suggesting that liquidity levels may have some impact on subsequent commodity futures returns. Finally, the coefficient on the hedging pressure factor loading β_i is significantly positive, as one might expect, consistent with the notion of a risk premium.

3.2 Time-Series Tests

In the spirit of the analysis in Ang et al. (2006) for equities, equation (1) can be exploited to sort commodities into quintiles based on their past idiosyncratic volatility levels. To illustrate with an example, let us focus on the strategy that models idiosyncratic volatility relative to the hedging-pressure benchmark with *R*=4 weeks and *H*=13 weeks. First, we extract the idiosyncratic volatility measure $\sigma_{\varepsilon,i}^{(4,13)}$ for each commodity *i*=1,…,*N* by estimating equation (1) over an initial 52-week window using

$HP_t^{(4,13)}$ as benchmark. The commodities are sorted according to $\sigma_{\varepsilon,i}^{(4,13)}$ and we focus on the bottom and top quintiles, respectively, a low idiosyncratic volatility portfolio (called, *LowIV*) and a high idiosyncratic volatility portfolio (called, *HighIV*). We buy *LowIV* (expecting a future increase in its returns), sell *HighIV* (expecting a future decrease in its returns) and hold this long-short portfolio for *H*=13 weeks. The process is repeated recursively to obtain new signals $\sigma_{\varepsilon,i}^{(4,13)}$ over a second window ending at observation 52+*H*, at which time another long-short portfolio is formed and held over *H* weeks and so on. Thus we obtain a sequence of active long-sort idiosyncratic volatility returns associated with the benchmark *R*=4 and *H*=13. Since there is no a priori reason to confine the strategy to ranking and holding periods of 4 and 13 weeks, respectively, we proceed similarly for all other hedging-pressure benchmarks reported in Table 1.

For consistency, both the hedging-pressure benchmarks and the idiosyncratic volatility portfolios use 20% of the total cross-section[6], and equal weight is given to the constituents of each (top and bottom) quintile. The choice of equal weights follows from the literature on commodity futures markets (e.g. Erb and Harvey, 2006; Gorton and Rouwenhorst, 2007, inter alios). Equal weights are convenient to avoid portfolio concentration on specific commodities thus ensuring better diversification. However, this weighting scheme can cause illiquidity problems, making it difficult for investors to open or close their positions. We will confront the liquidity issue explicitly in Section 5.

The performance of the idiosyncratic volatility portfolios, summarized in Table 3, suggests that the finding in Ang et al. (2006, 2009) of a positive return spread between low and high idiosyncratic volatility assets also extends to commodity markets. In line with a negative relationship between lagged idiosyncratic volatility and future returns, the *LowIV* portfolios earn positive (albeit statistically insignificant) mean returns ranging from 3.21% to 4.43% a year while the *HighIV* portfolios earn negative (albeit statistically insignificant) mean returns ranging from -8.29% to -5.16% a year.[7]

[Insert Table 3 around here]

[6] The choice of quintiles follows from Ang et al. (2006, 2009) but similar conclusions hold should the percentage of the cross-section included in the long (short) portfolio be set at 15%.

[7] This evidence is in line with Ang et al.'s (2006, 2009) findings for equities where it is also shown that the performance of the long-short portfolio is mostly driven by the negative average return of the high idiosyncratic volatility (short) portfolio.

Taking simultaneous (fully collateralized) long positions in commodities with low idiosyncratic volatility and short positions in commodities with high idiosyncratic volatility yields mean returns that range from 4.67% to 6.18% a year with an average at 5.49%. All 16 combinations of R and H periods generate positive and significant mean returns at the 5% level or better.

Raw returns are, however, crude performance indicators as they do not account for the natural propensity of commodity markets to be either in backwardation or contango. It is thus important to appraise performance on a risk-adjusted basis by means of the portfolio's *alpha* (α hereafter) relative to a suitable benchmark; in the present context α is obtained by regressing the returns of the active commodity strategy (i.e., long-short portfolio returns) on the hedging pressure risk premium.[8] Table 3 shows α of the long-short idiosyncratic volatility portfolios that ranges from 3.04% to 5.72% a year with an average at 4.62% and are thus economically significant. They are also statistically significant at the 5% (10%) level for 12 (15) of the 16 idiosyncratic volatility strategies considered. It is also reassuring that the performance of the idiosyncratic volatility strategies does not hinge on a priori choices of *R* and *H*: all cases yield positive mean returns at the 5% level and positive α. Indeed the dispersion (standard deviation and range) of the portfolio returns and α across *R*-*H* combinations is very small.

In order to make non-normality robust inferences on the 'alpha generation' ability of the idiosyncratic volatility strategies, we deploy the bootstrap testing approach suggested in Cuthbertson et al. (2008) as an alternative to the conventional OLS *t*-test on the significance of α. The empirical (bootstrap) distribution of the *t*-statistic is obtained by: *i*) running a regression of the weekly returns of the idiosyncratic volatility strategies on a constant and the hedging-pressure benchmark, *ii*) constructing *B* simulated return series under the null hypothesis using the estimated beta alongside the bootstrapped regression residuals, *iii*) running again the initial regression using each of the *B* bootstrapped return series which enables *B* alphas, $\{\hat{\alpha}_j^*\}_{j=1}^{B}$, and corresponding bootstrap distribution of the *t*-statistic $\{t(\hat{\alpha}_j^*)\}_{j=1}^{B}$, and *iv*) assessing the significance of the α computed from the original sample on the basis of this bootstrap distribution. The residuals are resampled so as to mimic the time-series dependence using a moving-

[8] The *R* and *H* pair adopted to gauge alpha matches that used to model idiosyncratic volatility.

block-bootstrap (MBB) with length L=10 weeks and in a way that preserves also the cross-section dependence across commodities (see Fuertes, 2008; Politis and Romano, 1994). This inference confirms all alphas as significant (except that corresponding to R=52 and H=4 weeks) at the 5% level as indicated in italics in Table 3. The results are robust to alternative block-length choices such as L={20,30} weeks.

Thus far the idiosyncratic volatility of commodity futures contracts was defined, using equation (1), relative to a hedging pressure benchmark based on the positions of, first, hedgers and, second, speculators. We now reiterate the procedure using plausible variants of this benchmark considered in Basu and Miffre (2011) which are built on: *i*) the positions of speculators solely, *ii*) the positions of hedgers solely, and *iii*) the positions of, first, speculators and, second, hedgers. At 4.78% on average and with range [3.60%, 6.03%] the abnormal performance of the idiosyncratic volatility strategy based on these alternative benchmarks is virtually identical to that reported in Table 3.

A further noteworthy finding is that the long-short idiosyncratic volatility strategies perform well even when the holding period of the long-short IV portfolios is lengthened to 104, 156 or 208 weeks (i.e., 2, 3 or 4 years). We use as benchmark the hedging pressure risk premium based on the positions of, first, hedgers and, second, speculators, for the 16 combinations of R and H shown in Table 1.[9] The results suggest that the "alpha generation" ability of the strategies remains attractive (significant at the 5% level) averaging out to 5.56% (H=104), 5.76% (H=156) and 6.88% (H=208) across the 16 combinations of ranking and holding periods used to model the commodity risk premium. The negative relationship between past idiosyncratic volatility and future mean returns thus holds over long, as well as short, horizons. This provides evidence that a behavioral explanation based on 'overreaction' whereby commodities with low idiosyncratic volatility perform well in the short- to medium-term and poorly in the long-term as the market corrects itself, is unlikely to hold.

[9] Since the holding period of the idiosyncratic volatility strategies exceeds one year, it is tempting to also set the holding period of the hedging pressure benchmarks to more than a year. We decided against this choice as inventory considerations preclude that commodity futures markets would stay in backwardation or contango for 2 to 4 years. Such long holding periods for the hedging pressure benchmarks are indeed not consistent with the fact that commodity futures markets switch from backwardation to contango as inventory levels change.

4. Momentum, Term Structure and Idiosyncratic Volatility

4.1. Portfolio Construction Methodology

The literature on commodity futures markets has shown that momentum and term structure (TS) signals are sources of abnormal returns when exploited in isolation (Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006; Miffre and Rallis, 2007) and in conjunction (Fuertes et al., 2010). We now test the proposition that the profitability of the idiosyncratic volatility strategies documented above can be further enhanced by additionally considering momentum and TS signals. The hybrid triple-sort methodology that overlays idiosyncratic volatility, momentum and TS signals is outlined next.

Let the notation *Sorting* i with i=1,2,3 represent either one of the following signals: i=1 for momentum, i=2 for TS, and i=3 for idiosyncratic volatility (IV) observed in a set of, say, N=100 commodities. First, we split the available cross-section based on *Sorting* 1 (momentum) into two portfolios, called *Winner* and *Loser*, using the median (50th percentile) as threshold. *Winner* and *Loser* thus contain each 50 commodities with, respectively, the highest and lowest past returns (on average over the former R weeks). Second, we extract from *Winner* and *Loser* two other portfolios, called *Winner_HighRoll* and *Loser_LowRoll*, based on *Sorting* 2 (term structure) using the corresponding 50th percentile in each case. *Winner_HighRoll* thus contains the 25 commodities with the highest past performance and highest average roll-returns[10] over the former R weeks and *Loser_LowRoll* contains the 25 commodities with the lowest past performance and lowest average roll-returns over the former R weeks. Third, we extract two final sub-portfolios from *Winner_HighRoll* and *Loser_LowRoll* based on *Sorting* 3 (IV) using their respective 80th percentiles: from the constituents of *Winner_HighRoll* we buy the 80% (or 20 commodities) with the lowest idiosyncratic volatility as modeled in (1) and from the constituents of *Loser_LowRoll* we sell the 80% (or 20 commodities) with the highest idiosyncratic volatility. The resulting long-short portfolio is held for H weeks; this triple-sort strategy is denoted Mom-TS-IV hereafter

[10] Roll-returns are measured as the difference in the logarithmic price of the front contract and the logarithmic price of the second nearest contract. We take the average of the roll-returns over the ranking period to sort the commodities according to their term structure signals.

There is no a priori reason to exploit the momentum, TS, and idiosyncratic volatility signals in this order so we consider two strategies which alternative orderings that use the same percentiles (80^{th} for IV, 50^{th} for momentum and 50^{th} for TS) as thresholds to form sub-portfolios; these are called Mom-IV-TS and IV-Mom-TS. This combination of percentiles is chosen so that the final long and short portfolios contain each 20% of the initial cross section. Thus the comparison with the single-sort idiosyncratic volatility strategy that focuses on quintiles is fair. Likewise, for comparability purposes, all the strategies considered (single- and triple-sorts) give equal weights to the constituents of the long-short portfolios. Other percentiles combinations are examined below.

4.2. Performance Evaluation and Risk Management of the Triple-Sort Strategy

Before deploying the hybrid triple-sort strategy, it makes sense to assess whether the double-sort Mom-TS strategy advocated by Fuertes et al. (2010) encompasses the idiosyncratic volatility strategy. Put in a simple question: do the idiosyncratic volatility signals contain any pricing "information" not already incorporated in the momentum and TS signals? In order to address this question, the left-hand side of Table 4 reports: *i*) Pearson correlation between the returns of the IV-only and Mom-TS strategies, *ii*) percentage of commodities shared by their long (short) portfolios over time, and *iii*) Spearman correlation between rank-order of performance across *R* and *H* combinations.

[Table 4 around here]

The correlation statistics are very low and there is mild overlapping in the commodity composition of the *LowIV* (*HighIV*) portfolios and the *Winner_HighRoll* (*Loser_LowRoll*) portfolios that are held long (short). Overall these results provide reasonable evidence to discard the conjecture that the idiosyncratic volatility measured according to equation (1) is fully driven by momentum or term structure signals.[11] This warrants the combination of idiosyncratic volatility signals with momentum/TS signals.

[11] We also compared the idiosyncratic volatility portfolios and the single-sort momentum and term structure portfolios with results analogous to those reported in Table 4; for instance, the Pearson return correlations, $\rho_{IV,Mom}$=0.056 and $\rho_{IV,TS}$=0.0966, are insignificant. An alternative methodology employed by Ang et al. (2006) to address a similar question in the context of equities consists in forming 5 momentum (or term structure) quintiles and then splitting each momentum (or term structure) quintile into 5 idiosyncratic volatility quintiles. This enables a

The right-hand side of Table 4 presents for the hybrid triple-sort strategies annualized mean returns and alphas; the latter are modeled relative to hedging pressure benchmarks presented in Table 1.[12] Irrespective of the *R*-*H* combination chosen and the order in which the three signals are exploited, the triple-sort strategies yield positive mean returns that are significant at the 5% level for all but two of the 48 strategies considered. On a risk-adjusted basis, the triple-sort strategies perform well with α equal to 5.59% a year on average and with 42 cases (out of 48) that offer significant α at the 5% level. As borne out by the low standard deviations (Table 4; last row) the triple-sort portfolios performance does not hinge on the specific choice of ranking and holding periods.

The mean return at 5.49% per annum afforded by our IV-only strategy can be increased to 7% by overlaying momentum and TS signals in a triple-sort strategy (c.f. Tables 3 and 4). Likewise, there is an attractive increase in α from 4.62% per annum for the IV-only strategy to 5.59% for the triple-sort strategies on average.

Figure 1 plots the future value of $1 invested in 5 long-short commodity portfolios: *i*) the IV-only strategy, *ii*) the HP benchmark, and *iii*) the triple-sort strategies Mom-TS-IV, Mom-IV-TS and IV-Mom-TS. Each of these portfolios gives equal weight to all 16 combinations of *R* and *H* periods. In line with our previous findings, the graph shows that combining the three signals adds value relative to exploiting the idiosyncratic volatility signals alone, and also vis-à-vis the HP risk premia.

[Insert Figure 1 around here]

We test the sensitivity of our results to the three percentiles used in the triple-sort strategy by allowing each of them to take values {40th, 50th,…,90th} with the restriction that the total number of commodities in each of the final long/short portfolios is roughly 20% of the initial cross-section. Figure 2 presents the annualized α of nine such cases alongside the annualized α of the single-sort idiosyncratic volatility strategy; as

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test for whether idiosyncratic volatility effects persist after controlling for term structure or momentum effects. This approach is unfeasible in the present context since our cross-section only includes 27 commodity futures.

[12] In line with Fuertes et al. (2010), we find that the Mom-TS strategy is more profitable than the individual momentum and term structure strategies. The average annualized α stands at 4.93% for the double-sort strategy, at 0.61% for the single-sort strategy based on momentum, and at 3.93% for the single-sort strategy based on term structure.

previously, the reported α*'s* are averages across the 16 combinations of ranking and holding periods. Interestingly, although all strategies present sizeable α, the triple-sort strategies outperform the single-sort strategy only when the idiosyncratic volatility signal is given somewhat more 'weight' than the momentum and term structure signals.

[Insert Figure 2 around here]

5. Robustness Analysis

We now conduct a battery of tests to establish that the profitability of the idiosyncratic volatility signal (whether in 'stand-alone' form or 'combined' with momentum and term structure signals) is robust to various theoretical issues.

5.1 Commodity Characteristics: Backwardation and Contango

Hirshleifer (1988) argues that idiosyncratic volatility should be priced in commodity futures markets because some traders are deterred from participating by high set-up costs. Bessembinder (1992) supports Hirshleifer's prediction by showing that idiosyncratic volatility conditioned on net hedging is indeed priced in commodity futures markets, e.g. long speculators receive a premium (in excess of the contract's systematic risk) for underwriting hedgers' risk of price fluctuation. It is important therefore for the present commodity futures trading analysis to test the extent to which net hedging explains the profitability of idiosyncratic volatility signals.

The left-hand side of Table 5 reports the sensitivities or *betas* (β) of the IV-only and Mom-TS-IV long-short portfolios to the hedging pressure risk premia. Consistent with the idea that the single and triple-sort strategies buy backwardated commodity futures and sell contangoed commodity futures, β is found to be significantly positive at the 1% level for the long-short portfolios. This result confirms that backwardation and contango explain part of the performance of idiosyncratic volatility strategies.

[Insert Table 5 around here]

To shed further light on this issue, the right-hand side of Table 5 presents the average hedgers' and speculators' hedging pressures separately for the *long* and *short* portfolios constituents over the holding periods of the active strategies. Relatively low hedgers' hedging pressure (net short hedgers) and relatively high speculators' hedging pressure (net long speculators) are signs of backwardated markets, while the opposite applies to contangoed markets where hedgers are deemed to be net long and speculators net short.

On average the speculators' hedging pressure of the *long* portfolios stand at 0.6476 and 0.6675 for the single and triple-sort portfolios, respectively. These hedging pressures clearly exceed those of the *short* portfolios (that stand at 0.5748 and 0.5544 on average) and the differential is significant at the 1% level for each of the 16 *R-H* combinations. The opposite is found for hedgers, i.e. their average hedging pressure is less for the *long* than the *short* portfolios and the gap is often significant. These findings confirm that the *long* (*short*) portfolios are made mostly of backwardated (contangoed) commodities.

To sum up, the evidence here presented suggests that in line with theory part of the returns of the idiosyncratic volatility portfolios relates to the natural propensity of commodity markets to be in backwardation or contango. Yet backwardation and contango cannot fully rationalize abnormal performance since α relative to hedging-pressure benchmarks (c.f Tables 3 and 4) is economically and statistically significant.

5.2 Is Performance Eroded by Transaction Costs?

The idiosyncratic strategies developed in Sections 3 and 4 are implemented on a small cross-section of commodities with a focus on the most traded (i.e. front-end) contracts that are relatively cheap and easy to short-sell. It is thus unlikely that the abnormal performance we have identified will be totally wiped out by the costs of implementing the strategies. To formally assess this issue, we re-construct the portfolios applying transaction costs of λ_{TC}={0.033%, 0.066%} per commodity trade. These figures are quite conservative in the light of Locke and Venkatesh's (1997) estimates for futures trading costs ranging between 0.0004% and 0.033% of notional value. The results presented in Figure 3 corroborate that the decline in abnormal performance is almost negligible. Net of reasonable transaction costs, the single-sort idiosyncratic volatility strategies still generate α of 4.6% (λ_{TC}=0.033%) and 4.5% (λ_{TC}=0.066%) per annum on average. The triple-sort strategies remain profitable too with average net α of 4.9% (λ_{TC}=0.033%) and 4.2% (λ_{TC}=0.066) per annum.

[Insert Figure 3 around here]

The fact that the net and gross α of the single-sort idiosyncratic volatility portfolios are indistinguishable from one another indirectly suggests that the trading intensity of the single-sort strategy is not especially detrimental on performance. This conclusion can also be extended to the triple-sort strategies that exploit idiosyncratic volatility, momentum and term structure signals despite their somewhat higher portfolio turnover.

To conduct this robustness check in a different way, we resort to breakeven transaction cost analysis which calculates the required level of cost per commodity trade in order to make the alpha of the strategy not larger than zero. Thus higher breakeven costs correspond with less trading-intensive strategies. On average across R-H combinations we obtain breakeven cost levels equal to 2.28% (StDev = 0.40) for the IV-only strategy and lower at 0.41% (StDev=0.22) for the three triple-sort strategies. These breakeven costs are substantially higher than Locke and Venkatesh's (1997) ceiling estimate at 0.033% per commodity trade. Hence, significant alpha remains after plausible levels of transaction costs are factored in. The unreported pattern of breakeven transaction costs across R-H combinations appears quite plausible since as H increases, for a fixed R, we rebalance less frequently and the breakeven costs increase uniformly.

5.3 Idiosyncratic Volatility or Liquidity Risk?

Han and Lesmond (2011) show for equities that the use of transaction prices induces liquidity effects (such as bid-ask bounce and zero returns) that artificially inflate idiosyncratic volatility. Once these liquidity effects are accounted for, the negative relationship between lagged idiosyncratic volatility and future mean returns vanishes. In the present commodity context where liquidity can be proxied by open interests the cross-sectional tests presented earlier offer preliminary evidence that idiosyncratic volatility is priced even after accounting for liquidity risk (c.f. Table 2). In this section we provide a more in-depth analysis of any link that may exist between the two.

We begin by assessing whether commodity futures with low idiosyncratic volatility tend to have low OI in relative terms. This conjecture is rather intuitive. Since investors demand a premium for holding assets that are relative illiquid (Pastor and Stambaugh, 2003), the better performance of the low idiosyncratic volatility portfolio could be driven by the low liquidity of its constituents and vice versa for the high idiosyncratic volatility portfolio. In Table 6 (Panel A) we report the ranking of commodities according to their average idiosyncratic volatility (IV)[13] and average OI over the entire sample. The Spearman rank-order correlation does not support the conjecture that commodities with low average IV tend to have low average OI; in fact, the rank-order correlation is negative albeit statistically insignificant. Clear examples are electricity, frozen pork bellies and random length lumber with very low average OI and very high average IV, and gold and soybeans with very high average OI and very low average IV.

[Insert Table 6 around here]

In Panel B of Table 6 the commodities are grouped into quintiles according to their average IV from low to high (first row) and their average OI from low to high (second row). The third row reports the percentage of commodities shared by the quintile with lowest IV and the quintile with lowest OI, and so forth. The results reveal no clear tendency for the commodities with low average idiosyncratic volatility to have lower average open interest. The percentages of shared commodities are indeed very small and often equal to zero. This preliminary analysis provides *prima facie* evidence that the superior performance of the low IV portfolios (relative to the high IV portfolios) cannot be attributed to a compensation for the relative lack of liquidity of their constituents.

Next the open interest (OI) averaged over a ranking period of R weeks is utilized as commodity sorting criteria in order to construct liquidity-driven active portfolios. Given that investors would demand higher returns as a compensation for lack of liquidity (Pastor and Stambaugh, 2003), our strategy buys the bottom quintile (called *LowOI)* and sell the top quintile (called *HighOI*); the resulting long-short portfolio is held for H weeks. The degree of overlapping between this liquidity-based strategy and our former idiosyncratic volatility strategy that buys *LowIV* and sell *HighIV* is gauged according to the Pearson correlation between their mean returns, and the percentage of commodities shared in the long/short portfolios over time. Table 6, Panel C, reports small absolute Pearson correlations between the weekly returns of the buy *LowIV* – sell *HighIV*

[13] The overall idiosyncratic volatility of a commodity is calculated by fitting equation (1) over the entire sample. Since the hedging-pressure benchmark is obtained for 16 combinations of R and H periods, we thus obtain 16 measures of annualized idiosyncratic volatility per commodity. The average of these 16 measures is what is presented in Table 6, Panel A.

portfolios and the buy *LowOI* − sell *HighOI*, in line with our previous findings. The percentage of commodities that are shared by the low IV and low OI portfolios is also very low; likewise for the high IV and high OI portfolios. This evidence suggests that *LowIV* (*HighIV*) is not tantamount to *LowOI* (*HighOI*) and hence, that liquidity risk is not fully what is being priced in our idiosyncratic volatility portfolios.

In a final attempt to control for liquidity risk, we redeploy the idiosyncratic volatility strategy by systematically excluding the 10% of commodities with the lowest average OI over the R weeks preceding portfolio formation. A caveat of this approach is that it further shrinks the already small original cross-section from 27 commodities which may further reduce the signal/noise ratio of our analysis. Notwithstanding this caveat, the average mean return and α of the idiosyncratic volatility strategy remain sizeable at 3.5% and 3.07% yearly, respectively. Overall the different tests in this section provide strong evidence against the notion that the outperformance of the long-short idiosyncratic volatility portfolio is an artifact of liquidity risk.

5.4 Data Snooping Bias

We now deploy Sullivan et al.'s (1999) Reality Check test in order to assess whether the profitability of the best trading rule in a large universe of rules is due to statistical chance rather than to a genuine merit in the strategy. This effect is known as data mining (or snooping) and it can arise when the same data set is exploited more than once for the purposes of inference. In essence, the Reality Check (RC) test evaluates whether the best strategy is significantly better than the benchmark by defining "significance" in terms of average performance from simulated (bootstrap) data sets.[14]

Suppose that we have S trading strategies and one common benchmark so the alpha of the strategy $s = 1,2, \dots, S$, minus the alpha of the benchmark is $\bar{\alpha}_s \equiv \alpha_s - 0$. The null

[14] A similar bootstrap approach (i.e., preserving the time-series and cross-section dependence) as in Section 3.2 is now deployed although here we resample the observed data as opposed to residuals. In addition to the weekly returns of each commodity, we bootstrap the weekly roll-return series that is required for the term structure strategy and the weekly HP data (hedgers' and speculators' positions) required to construct the bootstrap HP risk premium data. Each bootstrap HP risk premium series is used in the context of equation (1) together with the bootstrap return data to extract the IV signal at each iteration j=1,…,B with B= 500.

hypothesis of the RC test states that the alpha of the best strategy is no better than the alpha of the benchmark (fixed at zero) which can be formalized as follows

$$H_0 : \max_{s=1,2,..,S}\{\alpha_s\} \leq 0 \qquad (3)$$

and a significant test statistic (i.e., rejection) is interpreted as evidence that the best strategy outperforms the benchmark after controlling for data snooping bias. The test is accomplished by assessing the significance of the *supremum* statistic $\bar{W}_S = \max\{t_s\}_{s=1}^{S}$ with $t_s = \sqrt{n}(\alpha_s - 0)/\sqrt{Var(\alpha_s)}$ where n is the length of the portfolio return series. The significance of statistic $\bar{W}_S$ computed from the original sample is gauged on the basis of its empirical distribution, namely, the distribution of the centered bootstrap statistic $\{\bar{W}_{S,j}^{*}\}_{j=1}^{B}$ with $\bar{W}_{S,j}^{*} = \max\ \{t_{s,j}^{*} - t_s\}_{s=1}^{S}$ or equivalently its bootstrap *p*-value. Effectively, the RC test corrects downward the statistical significance of profitable trading strategies if the belong to a universe "dominated" by unprofitable rules; for an application of the RC test to the evaluation of technical trading in commodity futures see Marshall et al. (2008). We also consider a step-wise multiple test developed by Romano and Wolf (2005; denoted StepM) that has better power properties than the RC test. Whereas the null hypothesis of the RC test refers to the best trading rule in the universe of rules, the StepM can identify several profitable trading rules.

Our universe consists of the single-sort idiosyncratic volatility strategy, the triple-sort strategy Mom(50%)-TS(50%)-IV(80%) with alternative re-orderings (e.g. see Table 4) and the triple-sort strategies resulting from the alternative percentile combinations reported in Figure 2 with different re-orderings; the alpha of each strategy is averaged across *R* and *H* combinations. This brings the total number of strategies considered to *S*=28. We consider as common benchmarks the hedgers-speculators' hedging-pressure risk premia discussed in Section 2.2 and the three variants in Section 3.2 denominated speculators-only, hedgers-only, and speculators/hedgers' risk premiums. The *p*-values of the RC test for each of the four types of benchmarks, respectively, at 0.006, 0.002, 0.002 and 0.000, suggest that the best strategy has significantly positive alpha after accounting for data snooping. The StepM test identifies the single-sort IV reported in Table 3 and each of the triple-sorts reported in Table 4 as significantly profitable irrespective of the heding-pressure risk premia considered.

5.5 Idiosyncratic Volatility Trading during Tranquil and Turbulent Markets

Commodity and traditional bond and equity markets have experienced sharp increases in volatility over specific sub-periods of our 1992-2011 sample. For example, equity markets became highly volatile in the wake of the early 2000s dotcom bubble and after the disastrous collapse of Lehman Brothers in September 2008. Similarly, commodity prices have been gyrating wildly after the slowdown in worldwide economic activity triggered by the 2008 global financial crisis. Scenarios of high versus low *market* volatility provide an interesting laboratory to re-assess the profitability of our trading strategies. We define market volatility with reference to three asset classes: commodities, bonds and equities. Three conditional volatility series are obtained by fitting a GARCH(1,1) model to the weekly returns of, respectively, the S&P-GSCI, the JPMorgan US Government Bond Index and the S&P 500 Composite Index; the data sets are obtained from *Datastream*. We then define "tranquil" and "turmoil" regimes on the basis of the 5^{th} and 95^{th} percentiles of each volatility series. Table 7 shows the annualized returns of long-short idiosyncratic volatility portfolios (averaged across *R* and *H* pairs) and long-only portfolios (the S&P-GSCI and an equally-weighted portfolio of the 27 commodities) separately during each volatility regime.

[Insert Table 7 around here]

Irrespective of the asset class observed to define market volatility, in turmoil regimes investors are better off holding long-short commodity futures positions based on idiosyncratic volatility signals than being long-only. For example, when the conditional volatility of the S&P-GSCI exceeds 34.66% a year (an event that occurs 5% of the time by construction), the outperformance of the long-short portfolios relative to the long-only commodity portfolios stands at an average of 38.67% a year. Likewise, in turmoil regimes for bond and equity markets the mean returns of the long-short idiosyncratic volatility portfolios exceed those of the long-only commodity portfolios, respectively, by about 27.64% or 58.87% a year. This evidence is consistent with the notion that episodes of heightened market volatility (where "market" refers to either commodities, bonds or equities) are often associated with falling commodity futures prices, making long-short portfolios more profitable than long-only positions.

On the other hand, when the annualized conditional volatility of the S&P-GSCI is less than 12.45% (an event that occurs 5% of the time by construction), the long-short portfolios perform poorly relative to long-only commodity portfolios. But this conclusion does not extend to traditional asset markets, namely, the long-short portfolios remain attractive when bond and equity markets are in a tranquil state. To sum up, the superior performance of long-short portfolios vis-à-vis long-only portfolios prevails in both high and low volatility states in bond and equity markets.

A final important observation from Table 7 is that the single-sort strategy that exploits idiosyncratic volatility signals emerges as more robust to extremely high and low volatility markets than the triple-sort that additionally exploits momentum and TS signals. This is a reflection of the fact that the idiosyncratic volatility porfolios have better higher order moment properties than the momentum- and TS-based portfolios. In fact, the skewness and kurtosis of the IV-only portfolios are, respectively, -0.0218 and 3.3305 on average across R and H combinations whereas the counterpart statistics for the double-sort Mom-TS portfolios are -0.1338 and 3.4795. These findings indirectly bear out that idiosyncratic volatility signals are less contaminated by noise than momentum and TS signals during extreme (high/low) market volatility conditions.

5.6 Tactical versus Strategic Asset Allocation Roles

Aside from their role for *tactical* asset allocation, commodities are typical *strategic* asset allocation vehicles, namely, long-only commodity portfolios have attractive risk diversification and inflation hedging properties (Bodie and Rosansky, 1980; Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006). In this section we test whether these strategic allocation roles are preserved in our long-short commodity portfolios.

We begin by presenting in Table 8, Panel A, the correlations between the returns of our idiosyncratic volatility strategies and those of bonds and equities.[15] The analysis is based on *Datastream* data on the JPMorgan US Government Bond Index, JPMorgan US

[15] Earlier studies urged caution against the relative low signal/noise ratio inherent in weekly or daily sampling frequencies for testing the inflation-hedge effectiveness of commodities. Thus Bodie and Rosansky (1980) and Gorton and Rouwenhorst (2006) resort to quarterly data whereas Erb and Harvey (2006) use annual data. We adopt the former approach and convert into quarterly the weekly returns of our idiosyncratic volatility strategies.

Cash 3m Index, S&P 500 Composite Index, and Russell 1000 Index. Panel B presents similar information for the long-only S&P-GSCI and a long-only equally-weighted portfolio of the 27 commodities. For space constraints but without loss of generality, we only present results for the first four R-H combinations reported in previous tables.

[Insert Table 8 around here]

At -0.0300 and -0.0327 on average the correlations between equity markets (S&P 500 Composite Index, Russell 1000 Index) and our long-short commodity portfolios in Panel A are much lower than those with long-only commodity portfolios in Panel B (0.2065 and 0.2213). The correlations between fixed income indices (US Government Bond Index and US Cash 3m Index) and long-short commodity portfolios are higher (at -0.0172 and 0.0048 on average) than with long-only commodity portfolios (at -0.2694 and -0.2057). Overall the correlations are quite low confirming that, by tactically including long-short commodity positions into their asset mix, institutional investors can simultaneously earn an abnormal return and reduce the overall portfolio risk.

Second, we test whether our long-short commodity portfolios can be used as a hedge against unexpected inflation (UI). The latter is measured as the estimated errors of an ARMA(1,1) model fitted to logarithmic quarterly changes in US CPI data also from *Datastream*. The correlations between UI and the returns of the single-sort idiosyncratic volatility portfolios in Panel A of Table 8 average out at -0.2367 and are significant at the 5% level. As shown in Table 8, the correlations between the long-short portfolios and UI suggest that some ability (albeit small) to hedge inflation is shown by the triple-sort strategies but none for the single-sort strategy. However, the long-only commodity portfolios appear superior in this regard with the largest average correlation with UI at 0.4480. This evidence is in line with previous studies in suggesting that a downside of taking both long and short positions in commodity futures markets is to lose part, if not all, of the inflation hedge that naturally characterizes long-only commodity portfolios (e.g., see Miffre and Rallis, 2007).

6. Summary and Conclusions

The paper shows that the pricing ability of idiosyncratic volatility documented in international equity markets by Ang et al. (2006, 2009) also prevails in commodity markets. Our long-short active strategies that buy commodities with low idiosyncratic volatility and sell commodities with high idiosyncratic volatility earn on average an alpha of 4.62% a year which is economically and statistically significant. We also find that there is little overlap between the idiosyncratic volatility portfolios and the double-sort portfolios advocated by Fuertes et al. (2010) that jointly exploit momentum and term structure signals. This motivates us to combine the information embedded in idiosyncratic volatility, past performance and past roll-returns in a triple-sort. Systematically buying (shorting) commodities with low (high) idiosyncratic volatility, good (poor) past performance and high (low) average roll-returns generates annualized alphas of 5.59%. During turbulent market conditions the long-short idiosyncratic volatility strategies are shown to be more profitable than during tranquil periods, and remain substantially more attractive than long-only commodity portfolios. However, the triple-sort strategies are less attractive during extreme high/low market volatility scenarios. This finding reflects that momentum- and/or TS-based portfolios have less favourable higher moments than idiosyncratic volatility-based portfolios. Finally, we corroborate that the profitable long-short commodity portfolios retain the desirable risk diversification properties that are characteristic of long-only commodity indices albeit at the cost of losing the inflation hedge.

The fact that idiosyncratic volatility strategies appear profitable across both equity and commodity markets suggests that their performance might relate to the presence of a yet-to-be-specified risk factor that is common to both asset classes. Robustness tests show that this risk factor is not simply a proxy for transaction costs, liquidity risk, momentum and term structure effects, or the natural propensity of commodity markets to be either in backwardation or contango. We also establish that the profitability of idiosyncratic volatility strategies in commodity markets is not a manifestation of overreaction, nor an artifact of data mining and withstands various specifications of the risk-return relationship used to extract the idiosyncratic volatility signal. While we have ruled out many explanations *why* idiosyncratic volatility matters in commodity futures markets is yet another puzzle that warrants further research.

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Table 1. Risk premium of commodity futures.

The table reports summary statistics for the hedging pressure risk premium of Basu and Miffre (2011) which is based on the positions of first, hedgers and second, speculators using 40% of the cross-section available at the time of portfolio formation. R and H measured in weeks are, respectively, the ranking period over which the positions of hedgers and speculators are measured and the holding period over which the long (backwardation) short (contango) portfolios are held. Mean (μ) and standard deviation (StDev) are annualized. Sharpe is the ratio of its annualized mean to its annualized standard deviation. *, ** and *** denote significant at the 10%, 5% and 1% levels, respectively. *t*-statistics are based on heteroskedasticity and autocorrelation robust Newey-West (1987) standard errors.

	μ		$t(\mu)$	StDev	Sharpe
Panel A: Individual risk premium					
R = 4, H = 4	0.0328		1.11	0.1011	0.3243
R = 4, H = 13	0.0357	*	1.73	0.0959	0.3721
R = 4, H = 26	0.0473	**	2.10	0.0979	0.4832
R = 4, H = 52	0.0393		1.64	0.0947	0.4147
R = 13, H = 4	0.0304		1.39	0.0987	0.3081
R = 13, H = 13	0.0419	*	1.88	0.0976	0.4298
R = 13, H = 26	0.0690	***	3.06	0.0977	0.7063
R = 13, H = 52	0.0353		1.33	0.0961	0.3669
R = 26, H = 4	0.0583	**	2.06	0.0977	0.5967
R = 26, H = 13	0.0596	**	2.34	0.0989	0.6026
R = 26, H = 26	0.0672	**	2.79	0.0959	0.7010
R = 26, H = 52	0.0316		1.16	0.0912	0.3458
R = 52, H = 4	0.0712	***	3.19	0.0959	0.7433
R = 52, H = 13	0.0566	**	2.51	0.0958	0.5907
R = 52, H = 26	0.0267		1.18	0.0965	0.2763
R = 52, H = 52	0.0307		1.24	0.0925	0.3315
Average	0.0458			0.0965	0.4746
StDev	0.0155			0.0024	0.1584
Panel B: Long-only benchmarks					
S&P-GSCI	0.0428		0.81	0.8448	0.1965
Equally-weighted portfolio	0.0064		0.21	0.2273	0.0529

Table 2. Idiosyncratic volatility and commodity returns: cross-section analysis.

The statistics reported in this table pertain to sequential cross-section regressions, equation (2), of commodity futures returns at week $t+j$, $j=1,\ldots H$, where H is the length in weeks of each holding period, on various lagged factors. The table report averages of the coefficient estimates for each of the R-H combinations over different weeks. λ_0 is the intercept. λ_1 is the coefficient of past idiosyncratic volatility (IV) measured with information up to t. λ_2 is the coefficient of logarithmic open interest at t (OI1). λ_2^* is the log open interest averaged over the ranking weeks that immediately precede portfolio formation (OI2). λ_3 is the coefficient of past returns (denoted R(-1) below). λ_4 is the coefficient estimated loading $\beta_{i,t}$ on the hedging pressure benchmark (denoted β_{HP} below) obtained from the estimation of equation (1) and its reported significance t-ratio is based on standard deviations computed using Shanken's (1992) error-in-variables correction. All other t-ratios in the table are based on Newey-West (1987) standard errors. *, ** and *** denote significant at the 10%, 5% and 1% levels, respectively.

	Constant		IV		OI1		OI2			R(-1)		β_{HP}	
	100xλ$_0$	$t(\lambda_0)$	λ_1	$t(\lambda_1)$	*100xλ2*	$t(\lambda 2)$	*100xλ2**	$t(\lambda 2^*)$		*100xλ3*	$t(\lambda 3)$	*100xλ4*	$t(\lambda 4)$
Model 1	0.1740	7.74 ***	-0.0417	-6.47 ***								0.1369	2.61 ***
Model 2	0.1422	2.40 **	-0.0402	-5.91 ***	0.0027	0.52						0.1335	2.54 **
Model 3	0.1659	7.34 ***	-0.0388	-5.90 ***						-0.1575	-0.65	0.1436	2.89 ***
Model 4	0.1303	2.14 **	-0.0369	-5.32 ***	0.0032	0.61				-0.1790	-0.72	0.1346	2.81 ***
Model 5	0.0397	0.56	-0.0384	-5.05 ***			0.0128	2.10	**			0.1297	2.70 ***
Model 6	0.0188	0.26	-0.0352	-4.61 ***			0.0140	2.29	**	-0.0940	-0.35	0.1371	2.75 ***

Table 3. Idiosyncratic volatility and commodity returns: time series analysis.

The table reports annualized mean returns (μ) and annualized abnormal performance (α) for strategies that sort commodities into quintiles based on past idiosyncratic volatility (IV). R and H, expressed in weeks, refer to the ranking and holding periods of the hedging pressure benchmark that is used to model idiosyncratic volatility. H is also the holding period of the idiosyncratic volatility strategy. The strategies buy the bottom (low idiosyncratic volatility) quintile and sell the top (high idiosyncratic volatility) quintile. The resulting long-short position is maintained over H subsequent weeks. α is measured relative to the same hedging pressure benchmark as the one used to model idiosyncratic volatility. Italics denotes α significance according to the moving-block-bootstrap distribution with block length L=10 weeks. t-statistics are based on robust Newey-West (1987) standard errors.

	Low IV portfolio				**High IV portfolio**				**Long-short IV portfolio**			
	μ	$t(\mu)$	α	$t(\alpha)$	μ	$t(\mu)$	α	$t(\alpha)$	μ	$t(\mu)$	α	$t(\alpha)$
R = 4, H = 4	0.0406	1.46	0.0344	1.25	-0.0829	-1.73	-0.0800	-1.67	0.0618	2.79	*0.0572*	2.66
R = 4, H = 13	0.0389	1.39	0.0317	1.14	-0.0741	-1.57	-0.0664	-1.39	0.0565	2.62	*0.0490*	2.36
R = 4, H = 26	0.0376	1.33	0.0279	0.99	-0.0770	-1.64	-0.0676	-1.42	0.0573	2.64	*0.0478*	2.29
R = 4, H = 52	0.0341	1.22	0.0284	1.03	-0.0780	-1.68	-0.0708	-1.50	0.0561	2.65	*0.0496*	2.35
R = 13, H = 4	0.0389	1.39	0.0329	1.18	-0.0807	-1.71	-0.0765	-1.62	0.0598	2.74	*0.0547*	2.55
R = 13, H = 13	0.0364	1.30	0.0299	1.07	-0.0763	-1.63	-0.0677	-1.45	0.0564	2.64	*0.0488*	2.37
R = 13, H = 26	0.0355	1.26	0.0205	0.71	-0.0702	-1.50	-0.0592	-1.26	0.0529	2.44	*0.0399*	1.96
R = 13, H = 52	0.0321	1.14	0.0270	0.97	-0.0797	-1.73	-0.0739	-1.59	0.0559	2.65	*0.0504*	2.45
R = 26, H = 4	0.0398	1.44	0.0306	1.11	-0.0719	-1.49	-0.0580	-1.22	0.0559	2.51	*0.0443*	2.13
R = 26, H = 13	0.0390	1.39	0.0285	1.01	-0.0738	-1.56	-0.0653	-1.37	0.0564	2.59	*0.0469*	2.22
R = 26, H = 26	0.0354	1.26	0.0253	0.88	-0.0755	-1.60	-0.0648	-1.35	0.0554	2.54	*0.0450*	2.10
R = 26, H = 52	0.0328	1.16	0.0273	0.98	-0.0753	-1.60	-0.0698	-1.47	0.0540	2.50	*0.0486*	2.29
R = 52, H = 4	0.0418	1.46	0.0273	0.95	-0.0516	-1.03	-0.0336	-0.66	0.0467	2.00	0.0304	1.36
R = 52, H = 13	0.0405	1.40	0.0283	0.97	-0.0639	-1.26	-0.0501	-0.98	0.0522	2.21	*0.0392*	1.73
R = 52, H = 26	0.0351	1.21	0.0292	1.03	-0.0645	-1.28	-0.0595	-1.17	0.0498	2.13	*0.0444*	1.92
R = 52, H = 52	0.0443	1.43	0.0364	1.25	-0.0570	-1.13	-0.0489	-0.95	0.0507	2.16	*0.0426*	1.89
Average	0.0377		0.0291		-0.0720		-0.0633		0.0549		0.0462	
StDev	0.0034		0.0037		0.0087		0.0117		0.0037		0.0064	

Table 4. Triple-sort strategies based on idiosyncratic volatility, momentum and term structure.

The left-hand side of the table reports *i*) Pearson correlation between the weekly returns of the idiosyncratic volatility (IV) portfolios and double-sort momentum-term structure portfolios, *ii*) the percentage of commodities shared in the long and short portfolios on average over time and *iii*) Spearman correlation between the rank-order of mean returns across R-H combinations. R and H are ranking and holding weeks of the hedging pressure benchmark that is used to model idiosyncratic volatility. H is also the holding period of the active strategy. *, ** and *** denotes significant at the 10%, 5% and 1% levels. The right-hand side of the table reports annualized mean returns (μ) and annualized abnormal performance (α) for triple-sort strategies based on idiosyncratic volatility (IV), momentum (Mom) and term structure (TS) signals. The weights of each signal are 80%, 50% and 50%, respectively. α is measured relative to the same hedging pressure benchmark as the one used to model idiosyncratic volatility. Italics denotes α significance according to the moving-block-bootstrap distribution with block length L=10 weeks. t-statistics are based on robust Newey-West (1987) standard errors.

	Overlap between IV and Mom-TS			**Performance of Triple-Sort Strategies**											
	Pearson return	Shared commodities		Mom-TS-IV				Mom-IV-TS				IV-Mom-TS			
	correlation	*Long*	*Short*	μ	$t(\mu)$	α	$t(\alpha)$	μ	$t(\mu)$	α	$t(\alpha)$	μ	$t(\mu)$	α	$t(\alpha)$
R = 4, H = 4	0.0985 ***	0.0934	0.1718	0.0516	3.20	*0.0473*	2.91	0.0594	2.96	*0.0543*	2.67	0.0673	2.38	*0.0619*	2.15
R = 4, H = 13	0.1047 ***	0.0870	0.1855	0.0600	3.63	*0.0497*	3.14	0.0658	3.41	*0.0553*	2.86	0.0731	2.87	*0.0637*	2.36
R = 4, H = 26	0.0512 *	0.0941	0.1706	0.0552	3.04	*0.0434*	2.57	0.0618	2.94	*0.0506*	2.37	0.0643	2.62	*0.0550*	2.04
R = 4, H = 52	0.0557 **	0.0941	0.1882	0.0406	2.56	0.0377	2.37	0.0479	2.14	*0.0439*	1.96	0.0579	1.81	*0.0540*	1.69
R = 13, H = 4	0.1303 ***	0.0696	0.1771	0.0856	4.28	*0.0750*	3.87	0.0899	4.19	*0.0783*	3.78	0.0933	4.10	*0.0813*	3.69
R = 13, H = 13	0.1914 ***	0.0783	0.1681	0.0803	4.34	*0.0674*	3.87	0.0885	3.86	*0.0743*	3.33	0.0990	3.47	*0.0864*	2.94
R = 13, H = 26	0.1108 ***	0.0824	0.1647	0.0923	4.14	*0.0687*	3.28	0.0936	4.18	*0.0686*	3.24	0.0938	4.07	*0.0717*	3.22
R = 13, H = 52	0.0743 **	0.0706	0.2000	0.0527	3.09	*0.0456*	2.85	0.0599	2.74	*0.0516*	2.47	0.0659	2.53	*0.0590*	2.28
R = 26, H = 4	0.1593 ***	0.0537	0.1789	0.0912	4.29	*0.0713*	3.50	0.0961	4.47	*0.0754*	3.69	0.0931	4.00	*0.0720*	3.27
R = 26, H = 13	0.1695 ***	0.0551	0.1739	0.0670	2.58	*0.0462*	1.75	0.0670	2.95	*0.0455*	2.13	0.0582	2.92	*0.0370*	2.14
R = 26, H = 26	0.1175 ***	0.0529	0.1824	0.0644	2.31	*0.0432*	1.29	0.0610	2.88	*0.0391*	1.93	0.0493	2.94	0.0272	2.04
R = 26, H = 52	0.1363 ***	0.0706	0.1647	0.0548	2.24	*0.0492*	1.97	0.0577	2.74	*0.0522*	2.53	0.0468	2.64	*0.0401*	2.42
R = 52, H = 4	0.1019 ***	0.0389	0.1873	0.0974	3.37	*0.0701*	2.15	0.0803	3.39	*0.0530*	2.30	0.0763	3.97	*0.0468*	2.92
R = 52, H = 13	0.1531 ***	0.0328	0.1761	0.0870	3.33	*0.0634*	2.45	0.0800	3.34	*0.0575*	2.59	0.0773	3.49	*0.0538*	2.74
R = 52, H = 26	0.0705 ***	0.0364	0.1697	0.0732	2.83	*0.0627*	2.44	0.0721	3.22	*0.0616*	2.89	0.0634	3.15	*0.0525*	2.82
R = 52, H = 52	0.0131	0.0750	0.1625	0.0476	1.76	*0.0379*	1.38	0.0595	2.56	*0.0499*	2.21	0.0417	2.00	0.0320	1.64
Spearman rank corr	0.1706														
Average	0.1086	0.0678	0.1763	0.0688		0.0549		0.0713		0.0569		0.0700		0.0559	
StDev	0.0479	0.0207	0.0103	0.0181		0.0129		0.0148		0.0116		0.0178		0.0169	

Table 5. Backwardation and contango.

The left panel of the table presents the sensitivities (β) of the single and triple-sort strategies to the hedging-pressure risk premia. IV-only denotes the single-sort idiosyncratic volatility strategy, Mom-TS-IV denotes the triple-sort strategy based on first, momentum, second, term structure and, third, idiosyncratic volatility signals. The second and third panels report the average hedging pressure of speculators and hedger for the constituents of the *Long* and *Short* portfolios over the holding periods of the IV-only and Mom-TS-IV strategies. R and H are ranking and holding weeks of the hedging-pressure benchmark that is used to model idiosyncratic volatility. H is also the holding period of the idiosyncratic volatility strategy. *p*-value is for the null hypothesis that the hedging pressure of the *Long* and *Short* portfolio are identical.

	Hedging pressure beta				**Average hedging pressure of speculators**						**Average hedging pressure of hedgers**					
	IV-only		Mom-TS-IV		IV-only			Mom-TS-IV			IV-only			Mom-TS-IV		
	β	$t(\beta)$	β	$t(\beta)$	*Long*	*Short*	*p*-value	*Long*	*Short*	*p*-value	*Long*	*Short*	*p*-value	*Long*	*Short*	*p*-value
R = 4, H = 4	0.1621	3.81	0.1913	4.46	0.6488	0.5746	0.00	0.6946	0.5381	0.00	0.4305	0.4378	0.01	0.3952	0.4579	0.00
R = 4, H = 13	0.1729	3.79	0.2179	5.01	0.6483	0.5741	0.00	0.6771	0.5531	0.00	0.4312	0.4362	0.09	0.4042	0.4425	0.00
R = 4, H = 26	0.1939	4.31	0.1887	4.44	0.6485	0.5733	0.00	0.6621	0.5666	0.00	0.4319	0.4363	0.15	0.3994	0.4494	0.00
R = 4, H = 52	0.1625	3.70	0.0988	2.14	0.6462	0.5740	0.00	0.6465	0.5748	0.00	0.4324	0.4342	0.55	0.4144	0.4513	0.00
R = 13, H = 4	0.1534	3.39	0.3579	8.13	0.6471	0.5753	0.00	0.7079	0.5247	0.00	0.4308	0.4375	0.02	0.3911	0.4559	0.00
R = 13, H = 13	0.1682	3.99	0.2804	6.82	0.6465	0.5746	0.00	0.6754	0.5389	0.00	0.4308	0.4368	0.04	0.4078	0.4487	0.00
R = 13, H = 26	0.1811	4.22	0.3076	6.94	0.6463	0.5764	0.00	0.6544	0.5529	0.00	0.4321	0.4353	0.28	0.4126	0.4419	0.00
R = 13, H = 52	0.1658	3.65	0.2071	4.89	0.6451	0.5732	0.00	0.6317	0.5768	0.00	0.4311	0.4357	0.12	0.4231	0.4292	0.03
R = 26, H = 4	0.2160	4.97	0.3963	9.05	0.6458	0.5789	0.00	0.6929	0.5323	0.00	0.4318	0.4345	0.38	0.3981	0.4525	0.00
R = 26, H = 13	0.1637	3.61	0.3669	8.42	0.6457	0.5773	0.00	0.6752	0.5541	0.00	0.4318	0.4367	0.10	0.4021	0.4447	0.00
R = 26, H = 26	0.1662	3.62	0.3539	7.58	0.6452	0.5755	0.00	0.6603	0.5668	0.00	0.4322	0.4368	0.12	0.4059	0.4405	0.00
R = 26, H = 52	0.2099	4.70	0.2599	5.80	0.6480	0.5723	0.00	0.6334	0.5765	0.00	0.4296	0.4362	0.02	0.4251	0.4351	0.00
R = 52, H = 4	0.2276	4.77	0.4114	10.81	0.6504	0.5752	0.00	0.6750	0.5475	0.00	0.4278	0.4416	0.00	0.4044	0.4505	0.00
R = 52, H = 13	0.2203	4.65	0.3971	9.65	0.6496	0.5751	0.00	0.6634	0.5602	0.00	0.4280	0.4418	0.00	0.4090	0.4429	0.00
R = 52, H = 26	0.1930	4.03	0.3876	9.50	0.6484	0.5728	0.00	0.6549	0.5709	0.00	0.4284	0.4423	0.00	0.4123	0.4373	0.00
R = 52, H = 52	0.2815	6.93	0.3383	7.63	0.6521	0.5745	0.00	0.6496	0.5941	0.00	0.4262	0.4419	0.00	0.4134	0.4329	0.00
Average	0.1899		0.2976		0.6476	0.5748		0.6659	0.5580		0.4304	0.4376		0.4074	0.4446	

Table 6. Idiosyncratic volatility and liquidity risk.

Panel A sorts commodities by average idiosyncratic volatility (IV) and average open interest (OI) over the sample period and reports the Spearman rank-order correlation. Panel B groups commodities in quintiles from low to high idiosyncratic volatility and reports the average IV and OI in each quintile; the last row reports the percentage of shared commodities in the quintiles obtained according to average IV (from low to high) and the quintiles according to average OI (from low to high). Panel C measures the overlap between idiosyncratic volatility (IV)-based portfolios and open interest (OI)-based portfolios through Pearson return correlation and percentage of shared commodities in the long/short portfolios. *, ** and *** denotes significant at the 10%, 5% and 1% levels.

Panel A: Ranking of commodities

Low to high average IV		Low to high average OI	
Commodity futures	IV	Commodity futures	OI
Feeder cattle	0.1447	Electricity	2,234.64
Live cattle	0.1519	Frozen pork bellies	2,568.56
Gold	0.1592	Random length lumber	2,702.12
Platinum	0.2092	Rough rice	4,617.61
Soybean oil	0.2367	Oats	5,958.60
Soybeans	0.2399	Palladium	6,986.49
Lean hogs	0.2614	Feeder cattle	7,884.38
Cotton n°2	0.2715	Platinum	11,811.18
Copper	0.2717	Frozen concentrated orange	12,780.58
Rough rice	0.2718	Copper	13,271.42
Corn	0.2724	Lean hogs	27,733.13
Soybean meal	0.2725	Cocoa	29,205.38
Silver	0.2770	Cotton n°2	33,137.87
Wheat	0.2865	Coffee C	33,594.58
Cocoa	0.3059	Soybean meal	38,945.57
Sugar n° 11	0.3144	Heating oil n° 2	43,389.38
Oats	0.3165	Soybean oil	48,569.36
Frozen concentrated orange	0.3179	Silver	51,000.08
Random length lumber	0.3182	Blendstock RBOB gasoline	54,401.32
Heating oil n° 2	0.3224	Live cattle	56,847.26
Light sweet crude oil	0.3364	Natural gas	59,557.16
Frozen pork bellies	0.3408	Wheat	80,914.31
Palladium	0.3437	Soybeans	86,662.13
Blendstock RBOB gasoline	0.3757	Gold	108,612.75
Coffee C	0.3810	Sugar n° 11	142,239.78
Electricity	0.4405	Light sweet crude oil	161,092.84
Natural gas	0.4644	Corn	216,874.07
Spearman rank-order corr	-0.1569		

Panel B: Grouping of commodities

Quintiles	Q1	Q2	Q3	Q4	Q5
Average IV	0.0250	0.0365	0.0405	0.0454	0.0556
Average OI	3616.31	10546.81	32523.31	50841.48	143096.31
Shared	0.00%	20.00%	28.57%	0.00%	0.00%

Panel C: Overlap between IV-based and liquidity-based strategies

	Pearson return correlation	Shared comm long position	Shared comm short position
R = 4, H = 4	-0.3019 ***	0.1084	0.0211
R = 4, H = 13	-0.2997 ***	0.1159	0.0232
R = 4, H = 26	-0.2928 ***	0.1412	0.0235
R = 4, H = 52	-0.2716 ***	0.1059	0.0353
R = 13, H = 4	-0.3187 ***	0.1225	0.0106
R = 13, H = 13	-0.3163 ***	0.1275	0.0203
R = 13, H = 26	-0.3032 ***	0.1471	0.0235
R = 13, H = 52	-0.2530 ***	0.1412	0.0353
R = 26, H = 4	-0.3114 ***	0.1189	0.0070
R = 26, H = 13	-0.3246 ***	0.1217	0.0029
R = 26, H = 26	-0.3251 ***	0.1235	0.0000
R = 26, H = 52	-0.3149 ***	0.1176	0.0000
R = 52, H = 4	-0.2720 ***	0.1231	0.0335
R = 52, H = 13	-0.2837 ***	0.1313	0.0328
R = 52, H = 26	-0.2709 ***	0.1333	0.0303
R = 52, H = 52	-0.2518 ***	0.1250	0.0375
Average	-0.2945	0.1253	0.0211
StDev	0.0245	0.0114	0.0132

Table 7. Commodity portfolio returns during high and low market volatility periods.

The table presents the annualized mean returns of long-only and long-short commodity portfolios in periods of extreme volatility in commodity, fixed income and equity markets, where the performance of the long-short idiosyncratic volatility portfolios is averaged across different combinations of ranking and holding periods. IV, Mom and TS stand for idiosyncratic volatility, momentum and term structure, respectively.

Volatility regimes	Annualized volatility level	Annualized mean returns of commodity portfolios					
		Long-short				Long-only	
		IV-only	Mom-TS-IV	Mom-IV-TS	IV-Mom-TS	S&P-GSCI	Equal-weights
Commodity market: S&P-GSCI							
Low : below 5th percentile	< 12.45%	0.0123	-0.0376	-0.0384	-0.0375	0.1247	0.1853
High : above 95th percentile	> 34.66%	0.2573	0.1353	0.1698	0.1630	-0.1242	-0.2865
Fixed income market: JPMorgan US Gov Bond index							
Low : below 5th percentile	< 3.75%	0.2113	0.0220	0.0265	0.0145	-0.1576	-0.2536
High : above 95th percentile	> 6.6%	0.2484	0.2107	0.2393	0.2488	-0.0201	-0.0591
Equity market: S&P 500 Index							
Low : below 5th percentile	< 9.82%	0.1177	0.0292	0.0377	0.0177	0.0926	0.1596
High : above 95th percentile	> 29.53%	0.1859	0.0967	0.1351	0.1222	-0.2879	-0.6196

Table 8. Idiosyncratic volatility portfolios, traditional asset classes and unexpected inflation.

The table reports pairwise Pearson correlation coefficients and *p*-values between quarterly returns of commodity portfolios, and those of two traditional asset classes, fixed income and equity. The last row reports correlations between quarterly returns and quarterly unexpected inflation; the latter is proxied by the residuals of an ARMA model fitted to CPI inflation.

	Correlation	*p*-value	Correlation	*p*-value	Correlation	*p*-value	Correlation	*p*-value
Panel A: Long-short commodity portfolios								
	R = 4, H = 4		**R = 4, H = 13**		**R = 4, H = 26**		**R = 4, H = 52**	
	IV-only							
US Govt Bond Index	0.1370	0.1327	-0.1105	0.1848	-0.0618	0.3084	-0.0286	0.4084
US 3m Cash Index	0.0976	0.2143	-0.0794	0.2600	-0.0336	0.3927	-0.0122	0.4607
S&P 500 Index	0.0632	0.3043	-0.1097	0.1866	-0.0100	0.4677	0.0183	0.4411
Russell 2000 Index	0.1032	0.2011	-0.0828	0.2509	-0.0400	0.3731	-0.0219	0.4297
Unexpected Inflation	-0.2676	0.0137	-0.2370	0.0258	-0.2184	0.0368	-0.2239	0.0332
	Mom-TS-IV							
US Govt Bond Index	0.1363	0.1338	0.1129	0.1796	-0.1227	0.1594	-0.0854	0.2443
US 3m Cash Index	-0.1387	0.1297	0.0515	0.3384	0.0802	0.2579	0.0501	0.3424
S&P 500 Index	-0.1695	0.0835	-0.0527	0.3348	0.0195	0.4373	0.1255	0.1539
Russell 2000 Index	-0.1058	0.1952	-0.1239	0.1571	-0.0211	0.4322	0.0557	0.3261
Unexpected Inflation	0.0777	0.2645	0.1268	0.1513	0.2306	0.0292	0.2008	0.0503
	Mom-IV-TS							
US Govt Bond Index	0.1400	0.1275	0.0868	0.2408	-0.1856	0.0649	-0.1390	0.1291
US 3m Cash Index	-0.1344	0.1372	0.0534	0.3326	0.0957	0.2187	0.0875	0.2389
S&P 500 Index	-0.0786	0.2620	-0.0953	0.2198	-0.0960	0.2180	0.0101	0.4673
Russell 2000 Index	-0.1639	0.0908	-0.0657	0.2973	-0.0278	0.4110	0.0745	0.2730
Unexpected Inflation	0.0488	0.3465	0.0745	0.2730	0.2318	0.0286	0.1645	0.0901
	IV-Mom-TS							
US Govt Bond Index	0.1389	0.1293	0.1291	0.1471	-0.2659	0.0142	-0.1558	0.1022
US 3m Cash Index	-0.1017	0.2046	0.0646	0.3003	0.0048	0.4846	-0.0091	0.4707
S&P 500 Index	-0.1030	0.2017	-0.0232	0.4255	-0.0364	0.3841	0.0572	0.3217
Russell 2000 Index	-0.1182	0.1685	-0.0603	0.3125	-0.0024	0.4923	0.0772	0.2658
Unexpected Inflation	0.1561	0.1019	0.1242	0.1564	0.2256	0.0322	0.2305	0.0293
Panel B: Long-only commodity portfolios								
	S&P-GSCI		Equally-weighted					
US Govt Bond Index	-0.1751	0.0766	-0.3636	0.0012				
US 3m Cash Index	-0.1440	0.1207	-0.2674	0.0137				
S&P 500 Index	0.0697	0.2862	0.3433	0.0021				
Russell 2000 Index	0.0767	0.2671	0.3659	0.0011				
Unexpected Inflation	0.4620	0.0000	0.4341	0.0002				

Figure 1. Future value of $1 invested in long-short commodity futures portfolios.

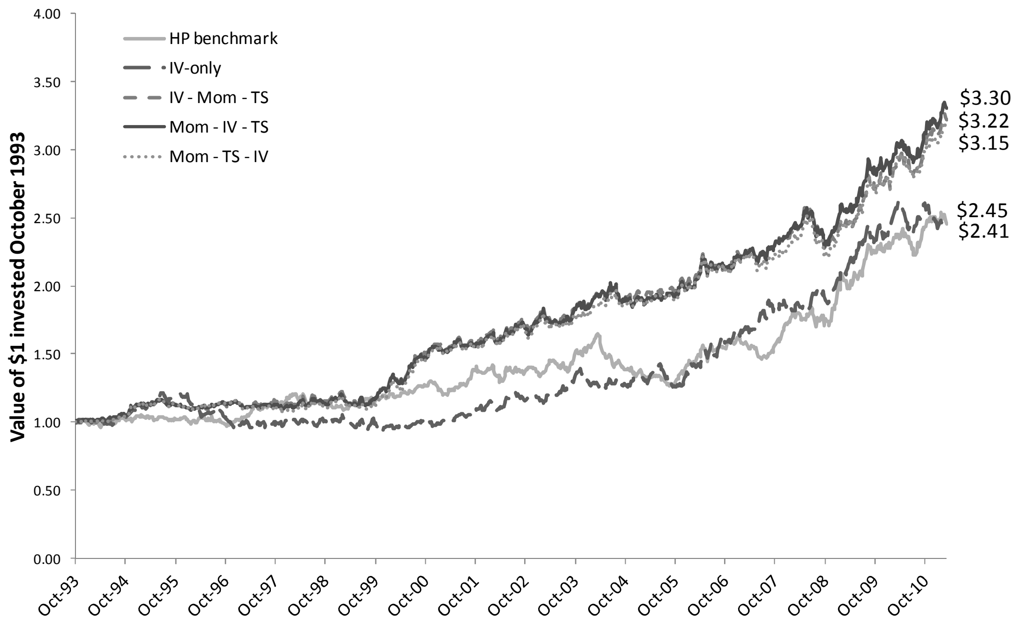

Figure 2. Performance of triple-sort strategies with alternative weight combinations.

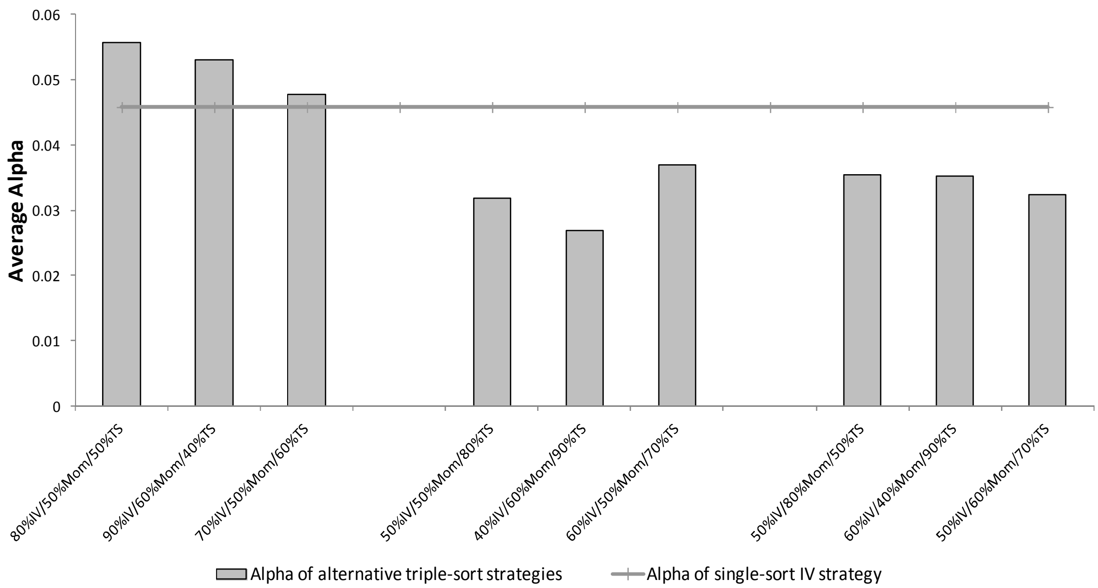

Figure 3. Impact of transaction costs.