Basis-momentum in the futures curve and volatility risk*

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Abstract

We propose a new commodity-return predictor related to the slope and curvature of the futures curve: basis-momentum. Basis-momentum strongly outperforms benchmark characteristics, such as basis and momentum, in predicting commodity spot and term premiums in the time series and cross section. The basis-momentum effect is varying within the curve of a single commodity, driven by roll returns, present in currency markets, and increasing in volatility – all consistent with maturity-specific price pressure. Asset pricing tests show that a parsimonious two-factor model provides an excellent cross-sectional fit, with a large premium for exposure to basis-momentum that largely represents compensation for volatility risk.

JEL Classification Codes: G12, G13.

Keywords: Term structure, commodity futures returns, maturity-specific price pressure, cross-sectional asset pricing, volatility risk.

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1 Introduction

The financialization of commodity markets since the early 2000s inspired a large amount of research and spurred the development of a wide range of commodity index investment vehicles, particularly aimed at institutional investors.[1] Initially, institutional investments were mostly passive, long-only, commodity futures strategies benchmarked to broad commercial indexes, as advocated in Erb and Harvey (2006) and Gorton and Rouwenhorst (2006). Recently, institutions follow increasingly active strategies that take both long and short positions and invest in both first-nearby and farther-from-expiring futures contracts.[2] For institutional investors and academics alike, it is important to understand what risks are behind the fundamental drivers of commodity futures return variation in the three most relevant dimensions: cross section, time series, and maturity.

Our contribution to the literature is threefold. First, we show that a new signal related to the slope and curvature of the term structure of futures prices, coined "basis-momentum", is the strongest predictor to date of commodity returns in all three dimensions. Second, we analyze what drives this predictability and argue that basis-momentum follows from maturity-specific price pressure and is related to volatility. Third, we find that exposure to a basis-momentum factor is robustly priced in the broadest cross-section of commodity returns studied to date, and argue that this price represents compensation for volatility risk. A parsimonious two-factor model, including basis-momentum next to a commodity market factor, provides an excellent cross-sectional fit relative to recently introduced commodity factor pricing models.

Basis-momentum is measured as the difference between momentum in first- and second-

[1] For work on the financialization: see, for instance, Irwin and Sanders (2011), Stoll and Whaley (2011), Tang and Xiong (2012), Cheng et al. (2014), Basak and Pavlova (2015), and Sockin and Xiong (2015). For work on commodity futures pricing in general: see, for instance, Hong and Yogo (2012), Yang (2013), Szymanowska et al. (2014), and Bakshi et al. (2015).

[2] Miffre (2013) contains an overview of so-called second- and third-generation commodity indexes. See, also, wsj.com/new recipes for commodity investing.

nearby futures strategies. A simple decomposition shows that basis-momentum is determined by average curvature and changes in the slope of the futures curve, which factors are commonly studied in the term structure literature. Given that the futures curve is typically steeper on the short end, it is natural that curvature predicts both nearby returns (from a first-nearby strategy) and spreading returns (from a strategy that combines a long position in nearby returns with a short position in second-nearby returns). For instance, average curvature is positive in backwardation, when first-nearby returns should be positive and larger than second-nearby returns. Likewise, persistence in the steepening (flatterning) of the slope should predict nearby returns in absolute terms and relative to farther-from-expiring returns. Cochrane (2011) similarly uses changes in book-to-market and dividend yield, instead of their more commonly used levels, to predict stock returns.

We perform three sets of tests and find results that are relevant for empiricists, theorists, and practitioners alike.[3] Our first set of tests serves to find out whether basis-momentum predicts commodity futures returns. We find that since the inception of commodity futures trading in 1959, basis-momentum strongly outperforms benchmark characteristics, such as basis and momentum, in predicting both nearby returns and spreading returns, in both the time series and cross section.[4] As shown in Szymanowska et al. (2014), nearby and spreading returns, respectively, capture spot and term premiums in commodity futures markets, analogous to the bond market. In the cross section, sorting commodities on basis-momentum leads to an economically and statistically large average annualized difference between the high and low portfolio of 18.38% (t-statistic of 6.73) in nearby returns and 4.08% (t-statistic of 6.43) in spreading returns.[5] These differences are robust in double sorts that control for basis, momentum, and a range of other variables. In pooled regressions that control for systematic

[3]Our main tests use a commonly studied sample of 21 commodities. The Internet Appendix shows robust evidence for an extended sample of 32 liquidly traded commodities.

[4]For empirical evidence on the basis (the difference between the futures and spot price) and momentum, see, e.g.,Miffre and Rallis (2007), Fuertes et al. (2010), Moskowitz et al. (2012), Yang (2013), Szymanowska et al. (2014), Koijen et al. (2015), and Bakshi et al. (2015).

[5]These returns survive estimates of transaction costs based on the evidence in Marshall et al. (2012).

differences across commodities, a standard deviation increase in basis-momentum predicts a large and significant increase in monthly nearby (spreading) return of 0.85% (0.2%).

Decomposing basis-momentum, we draw two additional conclusions. First, both average curvature and changes in the slope contribute to the performance of basis-momentum. Second, the restriction imposed by basis-momentum – that the difference between momentum measured at different points on the curve outperforms a single momentum measure – is supported in the data.

Our second set of tests serves to show that basis-momentum is consistent with maturity-specific price pressure and links basis-momentum to volatility along the lines of the framework in Brunnermeier and Pedersen (2009). We decompose futures returns in the part coming from appreciation of the underlying spot price and the part coming from rolling over the futures contract. Spot prices are impacted directly by storage and inventory decisions for the physical commodity (see Kaldor (1939), Working (1949), Deaton et al. (1992), and Gorton et al. (2013)), whereas roll returns follow from the shape of the futures curve and are mostly driven by hedger's price pressure in the futures market (Moskowitz et al. (2012) and Cheng and Xiong (2014)).[6] We find that basis-momentum exclusively predicts roll returns. Furthermore, basis-momentum predicts returns in a pure out-of-sample test for a cross section of 48 currencies, which can be stored costlessly. Finally, Gorton et al. (2013) argue that the returns to basis and momentum strategies in commodity markets are a compensation for bearing risk during times when inventories are low. The fact that basis-momentum predicts returns controlling for these benchmark characteristics thus reinforces our conclusion that basis-momentum is unlikely to be driven by storage and inventory dynamics.

A standard hedger's price pressure is not likely to explain our results either. The principal

[6]Cootner's (1960, 1967) hedging pressure theory (which is a reinterpretation of the theory of normal backwardation of Keynes (1930)), links futures risk premiums to the net demand of producers and consumers relative to speculators. Since hedging takes place in futures markets, hedger's price pressure affects futures prices and leads to a roll return as each futures price converges to the spot price at expiration. When short producers (long consumers) dominate the group of hedgers, the futures price is set below (above) the spot price and roll returns are positive (negative) in a backwardated (contangoed) market.

ideas of Cootner (1960, 1967) say nothing about spreading returns, whereas basis-momentum is only weakly correlated to hedging pressure measured using the Commitment of Trader reports of the Commodity Futures Trading Commission (CFTC).[7] Moreover, using returns of third- and fourth-nearby futures strategies, we show that basis-momentum predictability varies within the curve of a single commodity and is therefore maturity-specific.

In conclusion, we present the first evidence in the literature that is consistent with an extension of the traditional theory of hedger's price pressure, where maturity-specific price pressure obtains when the demand of hedgers relative to speculators varies persistently across contracts of a single commodity.[8] We cannot test this hypothesis directly using public CFTC data, because these data do not contain positions across the futures curve. Thus we leave for future work the question of what economic determinants are behind the imbalances in supply and demand of futures contracts that drive basis-momentum. However, there is clearly important information in the decisions of investors to establish a position at different locations on the futures curve. First, hedgers are not likely to invest only in the first-nearby contract when the maturity of their underlying exposure is beyond this contract's expiration, which relates to seasonality in production and demand. Further, commodity investors, and speculators in particular, are known to trade on information extracted from the shape of the futures curve. A position farther down the futures curve may also be attractive to reduce the number of roll dates and transaction costs. In fact, spreading positions are traded nowadays to ensure a continuous exposure at lower transaction costs and execution risk.[9] Second, time-varying volatility is a key determinant for the investment decisions of both hedgers and

[7]Existing evidence linking commodity returns to CFTC hedging pressure is mixed, however (see de Roon et al. (2000), Szymanowska et al. (2014), and Gorton et al. (2013)). Because the hedger classification of the CFTC has significant shortcomings (Cheng et al. (2014) and Dewally et al. (2013)), Acharya et al. (2013) proxy for hedging pressure using reported hedging policies and measures of default risk of firms in the oil and gas industry and find evidence consistent with the hedging pressure hypothesis.

[8]The same line of reasoning applies to currency markets, where price pressures follow from the trades of domestic hedgers with business or investments in the foreign currency, foreign hedgers with business in the domestic currency, and currency speculators that clear the market (see, also, Evans and Lyons (2002)).

[9]Most index providers mandate the existence of tradable spreading positions for a commodity to be included in an index (Neuhierl and Thompson (2014)).

speculators.[10]

Motivated by these observations, we investigate the relation between liquidity (or, price pressure), volatility, and basis-momentum. Among many others, Brunnermeier and Pedersen (2009) argue that when liquidity is tight, speculators become reluctant to take on positions that clear the market and volatility increases. Conversely, liquidity declines when fundamental volatility increases. (See Amihud et al. (2005) for an excellent review of the asset pricing implications of liquidity.) The model of Brunnermeier and Pedersen (2009) has two implications that we confirm in the context of the basis-momentum strategy. First, nearby and spreading returns on basis-momentum strategies are increasing in volatility. Here, we consider both aggregate and average commodity market volatility to ensure that we capture risk that is relevant for, respectively, diversified commodity investors and traditional hedgers and specialized speculators. Second, basis-momentum strategies expose investors to volatility risk, which suggests that basis-momentum is a priced risk factor in commodity markets.

Following this suggestion, our third set of tests serves to estimate the price of risk for exposure to a basis-momentum factor. For these tests we consider as test assets both nearby and spreading returns of either a range of portfolios (sorted on characteristics and sectors) or individual commodities. In this way, we contribute to a recent literature that constructs commodity factor pricing models to explain the cross-section of commodity returns, in the spirit of Fama and French (1993). In time series spanning regressions, the basis-momentum (nearby and spreading) factors provide a large and significant alpha relative to the three-factor models of Szymanowska et al. (2014) and Bakshi et al. (2015), which include commodity market, basis, and momentum factors. Further, cross-sectional asset pricing tests show that exposure to the basis-momentum nearby factor captures priced risk that is orthogonal

[10] See the traditional commodity futures pricing models of, e.g., Hirschleifer (1988, 1989) and Bessembinder and Lemmon (2002), as well as the equilibrium models of Routledge et al. (2000) and Kogan et al. (2009) that incorporate the downward sloping term structure of futures volatility.

from these benchmark factors at a Sharpe ratio ranging from 0.55 to 0.85 (depending on the specification).

In fact, a parsimonious two-factor model, including a commodity market factor and the basis-momentum factor, provides a cross-sectional fit that is similar to larger three- and four-factor models. Substituting a non-traded commodity market volatility risk factor for the basis-momentum factor worsens the cross-sectional fit only slightly. Since the price of volatility risk is consistent in magnitude with basis-momentum (at a Sharpe ratio of -0.65), these results support the interpretation that basis-momentum largely represents compensation for priced volatility risk. These results also imply that volatility risk is priced much more broadly in commodity markets than was previously known in the literature.[11] Evidence that volatility captures a negative price of risk is abundant in other asset classes (see, e.g., Ang et al. (2006) and Adrian and Rosenberg (2008) for stocks; and, Lustig et al. (2011) and Menkhoff et al. (2012a) for currencies).

The remainder of the paper is organized as follows. In Section 2, we describe the data and define the variables we use. In Section 3, we ask whether basis-momentum predicts commodity futures returns. In Section 4, we analyze how basis-momentum fits into commodity futures pricing theories and how it is linked to volatility. In Section 5, we run cross-sectional asset pricing tests. In Section 6, we summarize and conclude.

2 Data and variable definition

2.1 Commodity futures data

We collect data on exchange-traded, liquid commodity futures contracts from the Commodity Research Bureau, supplemented with data from the Futures Industry Institute. A substantial part of this dataset is identical to Szymanowska et al. (2014), who analyze returns

[11] Bakshi et al. (2015) and Koijen et al. (2015) focus on the link between commodity basis strategies and volatility risk.

on 21 commodity futures from 1986 to 2010. We extend this dataset in two directions. First, our sample starts in July 1959, at the inception of futures trading, and ends in February 2014. Second, we append data on eleven liquidly-traded commodities, among which some represent large markets, such as natural gas, gas-oil-petroleum, and sugar. Throughout, results for this larger sample are presented in the Internet Appendix.

We calculate monthly futures returns using a roll-over strategy. Our tests focus on returns from investing in first- and second-nearby contracts, because these are the most liquid. We present additional evidence for the third- and fourth-nearby contracts. For each of these contracts we calculate excess returns on a fully collateralized position using:

$$R^{T_n}_{fut,t+1} = \frac{F^{T_n}_{t+1}}{F^{T_n}_{t}} - 1, \tag{1}$$

where $F^{T_n}_{t+1}$ is the end of the month price of the nth-nearby futures contract ($n = 1, 2, 3, 4$), with expiration in month $t+T_n$. We follow Szymanowska et al. (2014) and restrict expiration to be after $t+2$. Thus, the nth-nearby strategy rolls into the $n+1$th-nearby contract at the end of month t, if the nth-nearby contract is expiring in month $t+2$. This approach avoids holding contracts close to expiration, when erratic price and volume behavior is commonly observed. Following recent work on commodities, our interest is in both long-only returns, where we will refer to $R^{T_1}_{fut,t+1}$ as the nearby return, and long-short returns, where we will typically refer to $R^{T_1}_{fut,t+1} - R^{T_2}_{fut,t+1}$ as the spreading return. We reverse the definition of spreading returns compared to Szymanowska et al. (2014) to facilitate interpretation of the results to come. Table A.1 of the Internet Appendix presents an overview of the commodity sample.

2.2 A decomposition of nearby and spreading returns

This subsection briefly summarizes the decomposition in Szymanowska et al. (2014) of expected futures returns in spot and term premiums, which are the object of our empirical analysis. Let us start from the definition of the futures price, $F_{t+1}^{T_n}$, in terms of the spot price of the underlying commodity, S_t, and the log or percentage basis, $y_t^{T_n}$:

$$F_t^{T_n} = S_t \exp\left(T_n \times y_t^{T_n}\right). \tag{2}$$

The collection $F_t^{T_n}$, $n = 1, 2, \ldots$, represents the term structure of commodity futures prices. For ease of exposition, we assume that $T_n = n$, such that, for instance, the first-nearby return can be calculated using the end of the month spot price.[12] We continue in logs, denoted by small letters.

We decompose the one-period expected log-spot return into the spot premium, $\pi_{s,t}$, and the one-period basis, y_t^1:

$$E_t[r_{s,t+1}] = E_t[s_{t+1} - s_t] = \pi_{s,t} + y_t^1. \tag{3}$$

It is natural to decompose the spot return into a premium and a component related to expected price appreciation. One would expect the spot price to increase over the life of the futures contract if $y_t^1 = f_t^1 - s_t > 0$. Next, we define a term premium, $\pi_{y,t}^{T_n}$, as the deviation from the expectations hypothesis of the term structure of the basis,

$$T_n \times y_t^{T_n} = y_t^1 + (T_n - 1)E_t[y_{t+1}^{T_n - 1}] + \pi_{y,t}^{T_n}. \tag{4}$$

Analogous to the bond market, these premiums can be earned using two common investment strategies. The expected return from an investment in the first-nearby futures contract delivers the spot premium:

$$E_t[r_{fut,t+1}^1] = E_t[s_{t+1} - f_t^1] = E_t[s_{t+1} - s_t - y_t^1] = \pi_{s,t}. \tag{5}$$

[12]The conclusions can be generalized if this is not the case.

The expected return from spreading strategies, which are long the first-nearby contract and short a futures contract with a longer maturity, deliver the term premiums. As a representative example, consider the second-nearby term premium, $\pi_{y,t}^{T_2}$. The expected return from a continuous investment in the second-nearby futures contract equals:

$$E_t[r_{fut,t+1}^{T_2}] = E_t[f_{t+1}^{T_2-1} - f_t^{T_2}] = E_t[(s_{t+1} - s_t) + (y_{t+1}^{T_2-1} - T_2 y_t^{T_2})] \tag{6}$$

$$= (y_t^1 + \pi_{s,t}) - (y_t^1 + \pi_{y,t}^{T_2}) = \pi_{s,t} - \pi_{y,t}^{T_2}, \tag{7}$$

such that

$$E_t[r_{fut,t+1}^{spread}] = E_t[r_{fut,t+1}^1] - E_t[r_{fut,t+1}^2] = \pi_{y,t}^{T_2}. \tag{8}$$

Considerable attention in commodity markets is given to the separation of futures returns into the component that comes from changes in the spot price of the commodity, and the roll return from rolling over the strategy every time a contract is (close to) expiring. We decompose expected first-nearby returns, as follows:

$$E_t[r_{fut,t+1}^1] = E_t[r_{fut,t+1}^{1,spot}] + E_t[r_{fut,t+1}^{1,roll}] = (\pi_{s,t} + y_t^1) + (-y_t^1), \tag{9}$$

where the expected spot return is equal to $E_t[r_{s,t+1}]$, and the roll return is the negative of the short-term basis. At time t, the (first-) nearby strategy rolls out of the expiring contract at the spot price, s_t, and into the (now) first-nearby contract at the futures price, f_t^1. We do not decompose the expected spreading return, because it does not contain a spot return component.[13]

[13]This result follows from the fact that the spot premium shows up in both the first- and second-nearby return, such that the expected spreading return contains only roll return components. Similarly, we do not decompose returns of farther-from-expiring contracts, because these contain both spot and term premiums.

2.3 *Variable definition*

A long history of literature shows that the basis (B_t) and momentum (M_t), respectively defined as

$$B_t = \frac{F_t^{T_2}}{F_t^{T_1}} - 1, \tag{10}$$

$$M_t = \prod_{s=t-11}^{t} (1 + R_{fut,s}^{T_1}) - 1, \tag{11}$$

predict nearby futures returns with a positive sign.[14] Szymanowska et al. (2014) find that spreading returns are also related to the basis, but not momentum.

In this paper, we are interested in a new signal, coined "basis-momentum", defined as the difference between momentum in the first- and second-nearby futures strategy:[15]

$$BM_t = \prod_{s=t-11}^{t} (1 + R_{fut,s}^{T_1}) - \prod_{s=t-11}^{t} (1 + R_{fut,s}^{T_2}). \tag{12}$$

The motivation for this signal is that it contains information about both the slope and curvature of the futures curve, which are determined by investor's decisions (producers, consumers, speculators, and, more recently, index investors) to take positions at different points on the curve. To see why, we use the definition of first- and second-nearby log futures

[14]Following previous literature, we measure the basis using two futures prices to safeguard against the use of illiquid spot prices.

[15]We follow previous literature and define momentum as the prior twelve-month return. Our results are robust to alternative windows ranging from three to 24 months as well as to skipping a month before portfolio formation. These results are available upon request.

returns in Equations (5) and (7), and write basis-momentum as

$$\begin{aligned}
\sum_{s=t-11}^{t} r^1_{fut,s} - \sum_{s=t-11}^{t} r^2_{fut,s} &= \sum_{s=t-11}^{t} (s_s - f^1_{s-1}) - \sum_{s=t-11}^{t} (f^1_s - f^2_{s-1}) \\
&= \sum_{s=t-11}^{t} (f^2_{s-1} - f^1_{s-1}) - \sum_{s=t-11}^{t} (f^1_s - s_s) \\
&= \sum_{s=t-11}^{t} b^2_{s-1} - \sum_{s=t-11}^{t} b^1_s \qquad (13)
\end{aligned}$$

where $b^1_t = f^1_t - s_t$ and $b^2_t = f^2_t - f^1_t$ represent the slope (basis) measured at two different points on the futures curve. Equation (13) decomposes basis-momentum into average curvature ($\sum_{s=t-11}^{t-1} b^2_s - \sum_{s=t-11}^{t-1} b^1_s$) and the change in slope ($b^2_{t-12} - b^1_t$).[16]

For most observations in our sample, the futures curve is steeper on the short end, i.e., $|b^2_t| < |b^1_t|$. As a result, average curvature is positive (negative) in backwardation (contango), when first-nearby returns should be positive (negative) and larger (smaller) than second-nearby returns. Persistence in the steepening (flatterning) of the slope should similarly predict nearby returns in absolute terms and relative to farther-from-expiring returns.

3 Does basis-momentum predict returns?

This section asks whether basis-momentum predicts returns in three dimensions of interest: cross section, maturity, and time series.

3.1 Univariate sorts

To determine whether basis-momentum predicts returns in the cross section and with maturity, we start by sorting 21 commodities into three portfolios (High4,Mid,Low4) from August 1960 to February 2014. High4 contains the four commodities with the highest ranked

[16] Similarly, we can decompose momentum into the average slope and a change in price: $\sum_{s=t-11}^{t} r^1_{fut,s} = \sum_{s=t-11}^{t} -b^1_{s-1} + (s_t - f^1_{t-12})$.

signal; Low4 contains the four commodities with the lowest ranked signal; and, Mid contains all remaining commodities (which number is time-varying). In each month $t+1$, we calculate equal-weighted nearby and spreading returns of the portfolios ($R^{T_1}_{BM,p,t+1}$ and $R^{T_1}_{BM,p,t+1} - R^{T_2}_{BM,p,t+1}$ for p=[High4,Mid,Low4]). Recall from Section 2.2 that expected nearby returns capture spot premiums, whereas expected spreading returns capture term premiums. Our main interest is in the High4-minus-Low4 portfolio, for which we present results for a sort on basis and momentum as a benchmark. Table 1 presents the results.

In Panel A, we see that average nearby returns for the High4-minus-Low4 portfolio are large and significant in all three sorts. However, the effect is largest for basis-momentum, both economically and statistically, at 18.38% ($t = 6.73$) relative to -10.61% ($t = -3.88$) for basis and 15.02% ($t = 4.61$) for momentum. For spreading returns in Panel B, we see a large and significant effect only for basis-momentum, with an average spreading return of 4.08% ($t = 6.43$) for the High4-minus-Low4 portfolio. For both nearby returns and spreading returns, the basis-momentum effect translates to a Sharpe ratio of about 0.9.

Table 1 further shows that nearby returns for both basis-momentum and momentum are robust pre- and post-1986. In contrast, the basis effect is only large and significant in nearby returns pre-1986. Spreading returns on the basis-momentum strategy are significant in both sample periods, but larger in magnitude post-1986. Figure 1 plots rolling twenty-year average returns for the three strategies and shows that basis-momentum typically outperforms basis and momentum. Table A.2 of the Internet Appendix shows consistent evidence for the larger set of 32 commodities. We conclude that all three signals contain information about nearby commodity futures returns in the cross section, but it is basis-momentum that predicts most strongly. Further, basis-momentum is the only robust predictor of spreading returns. The absence of an effect in spreading returns for basis and momentum is consistent with the fact that these signals are determined by the (average) slope of the futures curve, and not (directly) by its curvature (see Equation (13) and footnote 16).[17]

[17]Szymanowska et al. (2014) find that the basis predicts spreading returns, but these authors sample data

We now turn to the composition and stability of these sorts. Figure 2 shows the percentage of months in which a given commodity is present in the High4 and Low4 portfolio, respectively. Relative to the case of basis, the basis-momentum and momentum strategies are more diverse in composition. Figure 3 presents holding returns up to twelve months after sorting at the end of month t. We see that the basis-momentum effect (in both nearby and spreading returns) weakens as time passes, but remains significant until eleven months after the sorting date. In contrast, the momentum effect in nearby returns dies out quickly. The basis effect in nearby returns strengthens the first few months after sorting and remains significant until about ten months after sorting.

Given that similar basis and momentum strategies are already applied in practice (see footnote 2), we believe that basis-momentum returns survive transaction costs. To see why, consider the estimated average effective half-spread of 4.4 basis points in Marshall et al. (2012) for large commodity futures trades. Then, even conservatively assuming that basis-momentum requires the investor to turn over both his long and short position twelve times per year (due to rebalancing and rolling of expiring futures contracts), the total transaction cost would add up to $12 \times 2 \times 2 \times 4.4 = 211.2$ basis points, which is well below average nearby returns of over 18%. Even spreading returns of around 4% survive this conservative estimate, noting that spreading positions can be rebalanced with one trade given the availability of calendar spreads (see footnote 9). Moreover, Table 1 demonstrates that over 90% of the average spreading return of the High4-minus-Low4 basis-momentum strategy comes from the Low4 portfolio since 1986. Thus, solely trading the short leg will largely preserve the average return, but halve transaction costs.

at a lower bi-monthly frequency. A monthly frequency is more common, however (see, e.g., Yang (2013), Koijen et al. (2015), and Bakshi et al. (2015)).

3.2 Multivariate tests

Even though the average nearby returns for basis-momentum in Table 1 are relatively large, the difference with basis and momentum is not significant. To ensure that the basis-momentum effect exists net of these and other characteristics, we first perform independent double sorts in two basis-momentum groups (split at the median) and two control groups. The control groups are formed on the basis and twelve-month average basis (both split at zero), momentum (split at the median), and, finally, hedging and spreading pressure (also split at the median).[18]

Table 2 presents the results. Looking at the control variables, we see that only basis, average basis, and momentum provide a large and significant High-Low spread in nearby returns around 10%. Controlling for basis-momentum, however, lowers the High-Low spreads considerably in at least one basis-momentum group. In contrast, the basis-momentum effect in nearby returns remains large and significant in all control groups. This conclusion holds also for spreading returns. Next to basis-momentum, spreading returns are large and significant only for the sort on spreading pressure at -2.03% ($t = -4.31$). The fact that the total number of spreading positions of non-commercials predicts spreading returns has not been documented in the literature before. It is however consistent with the intuition that long-short spreading positions of speculators may cause differential price pressure in the futures curve.

Next, we consider the pooled regressions

$$R^{T_1}_{fut,i,t+1} = \lambda'_C C_{i,t} + a_{t+1} + \mu_i + e_{i,t+1} \text{ and} \tag{14}$$

$$R^{T_1}_{fut,i,t+1} - R^{T_2}_{fut,i,t+1} = \lambda'_C C_{i,t} + a_{t+1} + \mu_i + e_{i,t+1}. \tag{15}$$

[18] We use public CFTC data to define hedging pressure as the difference between the number of short and long positions of commercials as in de Roon et al. (2000), and (speculator) spreading pressure as the total number of non-commercial spreading positions. We scale both measures by the total position of commercials. Dictated by data availability, we are restricted to a shorter time series from 1986 onwards for these measures.

We start with a model that includes only basis-momentum, $C_{i,t} = BM_{i,t}$, and sequentially add time fixed effects (a_{t+1}), commodity fixed effects (μ_i), and the control variables basis and momentum (in which case $C_{i,t} = [BM_{i,t}, B_{i,t}, M_{i,t}]$). We cluster the standard errors in the time dimension.

These pooled regressions are interesting as they split the return predictability from basis-momentum in its passive and dynamic components (Koijen et al. (2015)). Without commodity and time fixed effects, $\lambda_{BM,t}$, represents the total return predictability from basis-momentum. Including time fixed effects removes the passive component coming from average commodity returns being high or low at a given point in time, analogous to a Fama and MacBeth (1973) regression. Including commodity fixed effects removes the passive component coming from unequal unconditional average commodity returns, which controls for systematic differences across commodity markets (due to investor's roll-over strategies, liquidity and market depth, seasonalities, and so on). For instance, Fama and French (1987) and Moskowitz et al. (2012) find that basis and momentum have predictive power for commodity returns in the time series.[19] By including both commodity and time fixed effects, the slope coefficient $\lambda_{BM,t}$ captures solely the dynamic component of basis-momentum return predictability.

Panel A of Table 3 presents the results for nearby returns. In isolation (column one), the coefficient estimate for basis-momentum is positive and significant at 10.45 ($t = 7.45$). This estimate is large economically and translates to an increase in monthly return of around 0.85% for a standard deviation increase in basis-momentum. Adding time fixed effects (column two) has little impact on the coefficient estimate, which is perhaps unsurprising given

[19]In the Internet Appendix, we also run individual time series regressions

$$R^{T_1}_{fut,i,t+1} = \delta_{0,i} + \delta_{BM,i} BM_{i,t} + e_{i,t+1} \text{ and} \tag{16}$$

$$R^{T_1}_{fut,i,t+1} - R^{T_2}_{fut,i,t+1} = \delta_{0,i} + \delta_{BM,i} BM_{i,t} + e_{i,t+1}. \tag{17}$$

Inspired by Moskowitz et al. (2012), we also estimate this regression using an indicator variable on the right-hand side that equals one when $BM_{i,t} > 0$.

the evidence from our sorts. More interesting is the similarly large and significant coefficient once we include commodity fixed effects (column three), which means that basis-momentum also predicts returns in the time series. Combining, the coefficient on lagged basis-momentum is large and significant at 9.16 ($t = 6.81$) when both fixed effects are included (column four). We conclude that that the dynamic component of basis-momentum predictability is dominant. In isolation, basis and momentum also predict nearby returns with a negative and positive coefficient, respectively (columns five and six). However, the dynamic component of basis-momentum predictability is robust to the inclusion of these benchmark predictors in a joint model (column seven). In contrast, the benchmark predictors are insignificant once basis-momentum is controlled for.[20]

In Panel B we see largely similar evidence for the predictability of spreading returns. In isolation (column one), the coefficient estimate for basis-momentum is positive and significant at 2.34 ($t = 6.89$). This estimate is economically large, as it translates to an increase in monthly spreading return of around 0.20% for a standard deviation increase in basis-momentum. Since the coefficient estimate is only slightly smaller once we control for both time and commodity fixed effects (column four), we conclude that the total spreading return predictability is also driven by the dynamic components of basis-momentum. Basis and momentum do not predict spreading returns.

The last two columns of Panels A and B show largely similar results for the two subsamples split around January 1986, whereas Table A.4 of the Internet Appendix shows similar evidence for the larger cross section of 32 commodities. Table A.5 of the Internet Appendix presents commodity-level time series regressions (see Eqs. (16) and (17)) to highlight which commodities drive the coefficient estimates in the pooled regression. In short, compared to basis and momentum, basis-momentum predicts nearby returns of a large number of commodities from various sectors. For spreading returns, the outperformance of basis-momentum

[20]Controlling instead for the twelve-month average basis as well as hedging and spreading pressure has little effect on the coefficient estimates for basis-momentum.

is even more outspoken.

In Panel C of Table 3, we present results for two decompositions of basis-momentum. First, we regress futures returns jointly on first- and second-nearby momentum (M_t and $M_t^{T_2} = \prod_{s=t-11}^{t}(1 + R_{fut,s}^{T_2}) - 1$) to see whether their coefficients are opposite in sign, as is imposed by basis-momentum. Second, we regress futures returns on average curvature and the change in slope (see Section 2.3), defined as:

$$Curv_t = \sum_{s=t-11}^{t-1} B_s^{T_2} - \sum_{s=t-11}^{t-1} B_s \tag{18}$$

$$\Delta Slope_t = B_{t-12}^{T_2} - B_t; \tag{19}$$

where B_t is the slope between the first- and second-nearby futures prices (as defined in Equation 11) and $B_t^{T_2} = \frac{F_t^{T_3}}{F_t^{T_2}} - 1$ is the slope between the second- and third-nearby futures prices.

We see that first- and second-nearby momentum significantly predict both nearby and spreading returns, with similar magnitude but with opposite sign (9.06 and -8.84 for nearby returns and 1.87 and -2.23 for spreading returns). The absolute magnitude of these coefficients is similar to the coefficient on basis-momentum in Panels A and B and we cannot reject the null that the three coefficients are equal at conventional levels of significance. We conclude that the restriction imposed by basis-momentum (i.e., that the difference in momentum predicts returns) is supported in the data. Next, we see that both average curvature and change in slope are (marginally) significant in predicting nearby and spreading returns, with the largest effect observed for average curvature. The economic magnitude of the coefficients is large, with an increase in monthly nearby (spreading) return of about 0.60% (0.16%) and 0.34% (0.05%) for a standard deviation increase in $Curv_t$ and $\Delta Slope_t$, respectively. We conclude that both components of basis-momentum contribute to its excellent performance as a predictor of commodity returns.

In all, the results of this section show that basis-momentum is the most powerful predictor to date of commodity futures returns in three dimensions of large interest: cross section, maturity, and time series. Basis-momentum predictability revolves around the dynamic components of spot and term premiums and is robust to controlling for known predictors. In fact, the performance of the previously known predictors is considerably less impressive once basis-momentum is controlled for. We conclude that basis-momentum should be a key input to empirical studies of commodity futures returns as well as to active commodity trading strategies.

3.3 Basis-momentum predictability across the futures curve

In this subsection we ask whether basis-momentum predictability is present throughout the futures curve. To this end, we first ask whether basis-momentum, as measured in Equation (12), is able to predict returns of the second- and third-nearby strategies ($R^{T_2}_{fut,t}$ and $R^{T_3}_{fut,t}$) as well as spreading returns between the second- and third-nearby and the third- and fourth-nearby strategies ($R^{T_2}_{fut,t} - R^{T_3}_{fut,t}$ and $R^{T_3}_{fut,t} - R^{T_4}_{fut,t}$). Next, we construct alternative measures of basis-momentum using these farther-from-expiring strategies, and ask whether these measures contain orthogonal information about returns. Using notation similar to before, we define

$$BM^{2,3}_t = \prod_{s=t-11}^{t} (1 + R^{T_2}_{fut,s}) - \prod_{s=t-11}^{t} (1 + R^{T_3}_{fut,s}), \text{ and} \tag{20}$$

$$BM^{3,4}_t = \prod_{s=t-11}^{t} (1 + R^{T_3}_{fut,s}) - \prod_{s=t-11}^{t} (1 + R^{T_4}_{fut,s}). \tag{21}$$

We sort commodities on the various basis-momentum signals to calculate average High4-minus-Low4 returns at various locations on the curve. Table 4 presents unconditional performance measures. In the first block of results, commodities are sorted on basis-momentum from Equation (12), which measure we used before. We note that farther-from-expiring futures returns are predictable with basis-momentum as well, but the effect weakens as the contract is farther from expiration. Compared to the results in Table 1, the performance of the High4-minus-Low4 portfolio is only slightly worse for $R^{T_2}_{fut,s}$ and $R^{T_2}_{fut,s} - R^{T_3}_{fut,s}$, translating to Sharpe ratios of 0.80 and 0.63, respectively. For $R^{T_3}_{fut,s}$ and $R^{T_3}_{fut,s} - R^{T_4}_{fut,s}$, the performance is again slightly worse, but still significant, economically and statistically.

In the remaining two blocks of results we sort commodities on $BM^{2,3}_t$ and $BM^{3,4}_t$. The first test in each block shows that these measures perform well in predicting returns of their respective contracts. For instance, sorting on $BM^{2,3}_t$ yields a High4-minus-Low4 portfolio Sharpe ratio of 0.92 and 0.68 for $R^{T_2}_{fut,s}$ and $R^{T_2}_{fut,s} - R^{T_3}_{fut,s}$, respectively. To ascertain that this result is not driven by a large correlation between basis-momentum measured at different points on the futures curve, the second test in each block zooms in on those months where $BM^{2,3}_t$ and $BM^{3,4}_t$ show little agreement with our standard measure of basis-momentum. To be precise, months with little agreement are those months where less than or equal to three (out of eight) commodities in the High4 and Low4 portfolios overlap between two alternative measures of basis-momentum. We see that even in these months the High4-minus-Low4 portfolios perform attractively with Sharpe ratios over 0.42 when investing in the farther-from-expiring futures strategies, with the exception of $R^{T_3}_{fut,s} - R^{T_4}_{fut,s}$. Table A.6 presents similar evidence for the larger sample of 32 commodities.

We conclude that basis-momentum measured at the short-end of the futures curve is able to identify that relatively near-to-expiring contracts will perform more attractively next month. However, basis-momentum also contains a significant maturity-specific component that varies across the short-, mid-, and long-end of the curve.

4 What drives basis-momentum and why does the effect persist?

In this section, we analyze how basis-momentum fits into existing commodity futures pricing theory. We argue that basis-momentum is driven by maturity-specific (hedger's) price pressure. Next, we analyze how the basis-momentum effect has persisted since the 1960s and argue that basis-momentum exposes investors to volatility risk.

4.1 Maturity-specific hedger's price pressure

Hedging pressure (Cootner (1960, 1967)) is a reinterpretation of the theory of normal backwardation of Keynes (1930). The basic idea is that futures risk premiums depend on the hedging demand of producers relative to consumers. If hedging is on aggregate short (long), futures prices are set below (above) the expected future spot price to convince risk-averse speculators to provide liquidity. In this paper, we consider an extension of this theory, because a standard hedger's price pressure is unlikely to explain our results. The principal ideas of Keynes and Cootner say nothing about spreading returns and maturity-specific effects, whereas we saw already that basis-momentum is robust to controlling for hedging pressure in cross-sectional tests.

We argue that if hedger's price pressure varies persistently across contracts of a single commodity, this could drive variation in both spot and term premiums. To test this hypothesis against alternative explanations based on storage and inventory dynamics, we ask whether return predictability from basis-momentum centers in roll or spot returns. Roll returns are mostly driven by imbalances in supply and demand of futures contracts from hedgers versus speculators that impact the shape of the futures curve, but not the spot price (see Moskowitz et al. (2012) and Cheng and Xiong (2014)). In contrast, spot returns are central to the theory of storage and directly affected by storage and inventory of the physical commodity. We also test whether basis-momentum exists in currency markets, where storage is not an issue. Before turning to these new tests, it is important to note that Gorton et al. (2013) argue that the returns earned on basis and momentum strategies are compensation for bearing risk during times when inventories are low. The fact that the basis-momentum effect is robust to controlling for these factors (see Tables (2) and (3)) is, thus, a first piece of evidence against storage- and inventory-based explanations.

4.1.1 Roll and spot returns

Table 5 presents results for the same sort as Table 1, but decomposes nearby returns in their spot and roll return components (see their definition in Section 2.2. Spot and roll returns for the first-nearby contract are calculated as:

$$R^{spot}_{fut,t+1} = \frac{1 + R^{T_1}_{fut,t+1}}{1 + R^{roll}_{fut,t+1}} - 1, \text{ where} \tag{22}$$

$$R^{roll}_{fut,t+1} = \begin{cases} \frac{F^{T_1}_t}{F^{T_2}_t} - 1, & \text{if } T_1 = t+2 \\ 0, & \text{otherwise.} \end{cases} \tag{23}$$

The first equation uses that, by construction, the futures return combines the spot and roll return.[21] In months that the strategy rolls, the roll return is calculated by dividing the price of the contract that you roll out of (the contract that expires in $t+2$) by the price of the contract that you roll into (and becomes the first-nearby contract). Roll returns are positive (negative) in a backwardated (contangoed) market, because the contract that you roll into has a lower (higher) price.

For basis-momentum, we see that the average return of the High4-minus-Low4 strategy, 18.38%, is almost completely driven by an average roll return of 21.53%. The average spot return is small and insignificant at -2.83%.Consistent with the fact that the nearby roll return is equal to the negative of the basis (see Equation (9)), we find an average roll return that is even larger for the sort on basis at -48.90%. Given this result, one might expect basis to be a better predictor of nearby futures returns than basis-momentum. We have already seen that it is not, however, with the average effect being smaller at -10.61%. This result is driven by strongly significant, but opposite, spot return predictability. Average spot returns for the

[21] Note that these returns are not tradable: roll and spot returns are the two components that make up the return to a rolling futures strategy.

basis strategy are 37.92%, consistent with the idea that futures prices contain information about expected future spot prices.[22] As a result, a large basis indicates that the market expects the spot price to increase over the life of the contract. This effect counteracts roll return predictability when predicting nearby futures returns. Interestingly, we find a similar, but weaker counteracting effect between spot and roll return predictability for the case of momentum.

Next, we run time series regressions of log holding period returns on lagged basis-momentum (following Fama and French (1987)):

$$r^{T_1}_{fut,i,t+1:t+T_1} = \eta_{0,i} + \eta_{BM,i} BM_{i,t} + v_{i,t+1:t+T_1}, \tag{24}$$

$$r^{roll}_{fut,i,t+1:t+T_1} = \eta^{roll}_{0,i} + \eta^{roll}_{BM,i} BM_{i,t} + v^{roll}_{i,t+1:t+T_1}, \text{ and} \tag{25}$$

$$r^{spot}_{fut,i,t+1:t+T_1} = \eta^{spot}_{0,i} + \eta^{spot}_{BM,i} BM_{i,t} + v^{spot}_{i,t+1:t+T_1}. \tag{26}$$

Note here that the left-hand side log returns are defined by the price difference of the first-nearby contract between two roll dates: t and $t+T_1$. As a benchmark, we also perform these regressions for basis and momentum.[23]

Table 6 contains an overview of the results, counting the number of positive and negative coefficients (that are significant at the 10%-level) for each predictor variable. Table A.7 of the Internet Appendix contains the full set of regression results. For a total of twelve out of 21 commodities, basis-momentum predicts nearby returns with a positive and significant coefficient. As in the cross section, this predictability is driven by roll returns, which basis-momentum predicts with a positive and significant coefficient in eighteen cases. In contrast,

[22] To see this, decompose the futures price in the expected futures spot price and a risk premium: $F^T_t = E_t[S_T] - E_t[P^T_t]$ (Eq. (4) in Fama and French (1987)). Now, decompose the futures return as $S_T - F^T_t = ([S_T - S_t] - E_t[S_T - S_t]) + E_t[P^T_t]$, i.e., the spot return plus a roll return that is exactly equal to the negative of the basis $(S_t - F^T_t)$. If market expectations are rational, one would indeed expect the basis to predict spot and roll returns with opposite signs. A negative covariance between the premium and (expected) spot returns, as observed in commodity data, further strengthens this effect (see, also, Koijen et al. (2015)).

[23] Fama and French (1987) notes the following equalities for the case of basis: $0 = \eta^{roll}_{0,i} = \eta^{spot}_{0,i} - \eta_{0,i}$ and $-1 = \eta^{roll}_{B,i} = \eta^{spot}_{B,i} - \eta_{B,i}$.

basis-momentum does not predict spot returns in more than a few cases. Consistent with Table A.5 of the Internet Appendix, the number of commodities for which basis-momentum predicts futures returns (twelve) is large relative to basis and momentum (six and four). Again, this result is driven by the fact that although basis and momentum predict roll returns even better than basis-momentum, they predict spot returns with the opposite sign.

We conclude that basis-momentum predictability is driven by roll returns, and not spot returns. This finding represent the second piece of evidence against storage- and inventory-based explanations of basis-momentum, but is possibly consistent with maturity-specific price pressure. In support of this conclusion, we have already shown that basis-momentum contains a maturity-specific component (see Table 4) and strongly predicts spreading returns that do not contain a spot return component (see footnote 13).

4.1.2 Basis-momentum in currency markets

Our currency sample is standard and contains 48 currencies from December 1996 to August 2015, for which we collect spot and one- and two-month forward exchange rates (S_{t+1}, F^1_{t+1}, and F^2_{t+1}, respectively, in US dollars per unit of foreign currency). A full description of the dataset and the data-cleaning procedure are found in Appendix A. We define monthly nearby and spreading currency returns as

$$r^1_{cur,t+1} = S_{t+1}/F^1_t, \text{ and} \tag{27}$$

$$r^{spread}_{cur,t+1} = r^1_{cur,t+1} - F^1_{t+1}/F^2_t. \tag{28}$$

As in the case of commodities, we sort these currency returns into three portfolios using basis-momentum, basis, and momentum.

Table 7 presents the results. In short, basis-momentum predicts currency returns. The nearby return of the High4-minus-Low4 portfolio is large and significant at 8.06% ($t = 3.47$). This return translates to a Sharpe ratio of 0.81, which is similar to what we find in the case of commodities in Table (1). The spreading return of the High4-minus-Low4 portfolio is significant as well at 0.78% ($t = 2.32$), translating to a Sharpe ratio that is slightly below what we find for commodities: 0.54.[24]

The existence of a basis-momentum effect in currency markets represents the third piece of evidence against storage- and inventory-based explanations, but can be explained in the context of maturity-specific price pressure. Domestic firms and investors with business in foreign currency want to sell foreign currency forward to hedge; foreign firms and investors with business in the domestic currency want to buy foreign currency to hedge; and, specialized speculators are there to clear the market. Thus, if there is persistent time-variation in the exposures of these groups of traders, this will lead to time-varying price pressures at different contract maturities and basis-momentum, in much the same way as in commodity markets.

4.2 Basis-momentum and volatility

To determine how the basis-momentum effect has been able to persist since the introduction of commodity futures trading, we ask how our strategies are related to volatility. A relation between maturity-specific price pressure and volatility can be motivated using the model of Brunnermeier and Pedersen (2009). These authors argue that when liquidity is tight, speculators become reluctant to take on positions that clear the market and volatility increases. Conversely, liquidity declines when fundamental volatility increases. This model has two implications that we test in the following: (i) higher volatility is related to more price pressure and thus higher future returns on basis-momentum strategies, and (ii) volatility is a state variable for risk premiums in commodity markets.

[24] In contrast to the case of commodities, basis outperforms basis-momentum in predicting currency returns. This evidence is consistent with an opposite relation between premiums and (expected) spot returns in commodity and currency markets (see footnote 22 and Koijen et al. (2015)). Because our focus is on commodity markets, we leave a thorough investigation of basis-momentum in currency markets to future work.

We consider both aggregate and average commodity volatility risk to ensure that the risk exposure is economically relevant for diversified commodity investors as well as traditional hedgers and specialized speculators. We compute aggregate commodity market variance in month t, var_t^{mkt}, as the sum of squared daily returns on an equal-weighted commodity index following the approach of Goyal and Welch (2008). We compute average commodity market variance in month t, var_t^{avg}, as the equal weighted average of the sum of squared daily returns of individual commodities. Both variance series are winsorized at the 1%-level, to reduce the impact of outliers, and standardized to accommodate interpretation.

We first test whether (the level of) variance predicts basis-momentum (nearby and spreading) portfolio returns using the regression:

$$R_{fut,p,t+1:t+k} = v_0 + v_{var} var_t + e_{t+1:t+k}, \tag{29}$$

where the left-hand side returns are compounded over horizons of $k = 1, 6, 12$ months. To conserve space, Panel A of Table 8 presents only the estimated coefficient, v_1, with its t-statistic computed using Newey-West standard errors with k lags, and the regression R^2. The first three rows show that aggregate commodity market variance predicts nearby returns (marginally) significantly at all horizons. The effect is economically large, with an annualized increase in the nearby return of the High4-minus-Low4 portfolio of, for instance, 7.56% for $k = 1$ and 5.78% for $k = 12$ for a standard deviation increase in variance. For spreading returns, the evidence is similar in significance and economic magnitude, with an increase in High4-minus-Low4 spreading return of, for instance, 0.85% for $k = 1$ and 1.27% for $k = 12$. The last three rows show largely similar evidence for our measure of average commodity market variance. We conclude that volatility predicts returns on basis-momentum strategies.

Next, we test whether basis-momentum (nearby and spreading) returns are exposed to innovations in these variance series:

$$R_{fut,p,t+1} = \nu_0 + \nu_{var} \Delta var_{t+1} + o_{t+1}, \tag{30}$$

where the innovation, Δvar_{t+1}, is measured as a first-difference.[25] Panel B of Table 8 present the results focusing on the estimated coefficient, ν_{var}. We see that exposures to innovations in aggregate commodity market variance decrease monotonically with basis-momentum in nearby returns. This pattern results in a significantly negative exposure of -8.65 ($t = -3.14$) for the High4-minus-Low4 portfolio, which translates to an annualized return of -9.58% for a one standard deviation innovation in Δvar^{mkt}_{t+1}. Exposures to innovations in average commodity market volatility are similar, translating to a significant increase in annualized return for the High4-minus-Low4 portfolio of -7.67% for a one standard deviation innovation in Δvar^{avg}_{t+1}. Finally, the exposures of the High4-minus-Low4 portfolio in spreading returns are also negative, but small and insignificant. We conclude that basis-momentum exposes both diversified and specialized commodity market investors to volatility risk, in particular through nearby returns.

In Table A.8 of the Internet Appendix, we present the same tests for basis and momentum. In short, the relation of these strategies with volatility is quite different from basis-momentum. Although basis and momentum are marginally exposed in nearby returns to innovations in volatility (albeit weaker than basis-momentum), neither nearby nor spreading returns are predictable by lagged volatility (in contrast to basis-momentum).

In all, the evidence for basis-momentum is most consistent with the model of Brunnermeier and Pedersen (2009) and, more particularly, our hypothesis of maturity-specific price pressure. When volatility is high, speculators are unwilling to provide liquidity and require a higher risk premium to clear the market especially for those futures contracts with largest

[25] The results are qualitatively robust to alternative specifications, such as estimating the innovations using an autoregressive model or using the sum of absolute returns to define the volatility series as in Menkhoff et al. (2012a).

(hedger's) price pressure. As a result, we also have that shocks to volatility contemporaneously depress most the prices of these futures contracts, which in turn leads to predictability in basis-momentum returns. Consistent with previous literature, these results suggest that volatility is an important state variable and captures a negative price of risk in commodity markets. In Section 5.3 we estimate the price of volatility risk directly in cross-sectional asset pricing tests.

5 Is basis-momentum a priced commodity risk factor?

In this section, we analyze the asset pricing implications from the basis-momentum strategy. Given that basis-momentum is an important driver of variation in commodity spot and term premiums and exposes investors to volatility risk, one might naturally expect exposure to basis-momentum to be priced. Following previous literature, we construct basis-momentum nearby and spreading factors as the High4-minus-Low4 portfolio return from a single sort on basis-momentum, denoted $R^{nearby}_{BM,t+1} = R^{T_1}_{BM,t+1}$ and $R^{spread}_{BM,t+1} = R^{T_1}_{BM,t+1} - R^{T_2}_{BM,t+1}$. We use similar notation for the nearby and spreading factors in benchmark commodity factor pricing models.

5.1 The basis-momentum factor

Panel A of Table 9 presents summary statistics for the two basis-momentum factors as well as five benchmark factors from the models of Szymanowska et al. (2014) (including three basis-related factors: $R^{nearby}_{B,t+1}$, $R^{spread}_{B,High4,t+1}$, and $R^{spread}_{B,Low4,t+1}$) and Bakshi et al. (2015) (including three nearby-return factors: $R^{nearby}_{B,t+1}$, $R^{nearby}_{AVG,t+1}$, and $R^{nearby}_{M,t+1}$). The latter model nests the two-factor model of Yang (2013), who leaves out the momentum factor. As noted in Table 1, the basis-momentum factors represent relatively attractive investment strategies relative to the benchmark factors. Further, the factors based on nearby returns are positively correlated, but no correlation is larger than 0.42. The correlations between factors based on nearby and spreading returns are even smaller, with the exception of $R^{nearby}_{BM,t+1}$ and $R^{spread}_{BM,t+1}$, with a correlation of 0.50. Thus, even though the cross section of commodities is small, the factors are sufficiently different to obtain independent variation over time.

In Panel B, we present spanning tests for the basis-momentum factors. In short, the two benchmark models do not go a long way in explaining the returns of the basis-momentum factors. For the basis-momentum nearby factor, the alpha is large and significant in both models at about 13% ($t > 5$), down from 18% in average returns. Moreover, the R^2 is only about 20% in both models, driven mostly by a large negative exposure to the nearby basis factor. Similarly, for the basis-momentum spreading factor, the alpha is large and significant in both models at about 3.5% ($t > 5$), down from 4% in average returns. Also, the R^2 is again below 20% in both models. The final two columns of the table demonstrate that these alphas are robust pre- and post-1986. Moreover, Table A.9 of the Internet Appendix shows similar evidence when the factors are constructed from the larger set of 32 commodities. We conclude that basis-momentum strategies provide an abnormal return.

5.2 Cross-sectional asset pricing tests with the basis-momentum factor

Next, we conduct cross-sectional regressions to estimate the price investors pay for exposure to basis-momentum. We consider a set of six candidate commodity factor pricing models that are nested in the model

$$\begin{aligned} R_{t+1} =& \gamma_{0,t} + \gamma_{1,t}\beta^{nearby}_{BM,t} + \gamma_{2,t}\beta^{nearby}_{B,t} + \gamma_{3,t}\beta^{nearby}_{AVG,t} + \gamma_{4,t}\beta^{nearby}_{M,t} + \\ & \gamma_{5,t}\beta^{spread}_{BM,t} + \gamma_{6,t}\beta^{spread}_{B,High4,t} + \gamma_{7,t}\beta^{spread}_{B,Low4,t} + u_{t+1}, \text{ or} \qquad (31) \\ R_{t+1} =& \gamma_{0,t} + \gamma'_t\beta_t + u_{t+1}. \qquad (32) \end{aligned}$$

The first specification is the model of Szymanowska et al. (2014) (setting $\gamma_{1,t} = \gamma_{3,t} = \gamma_{4,t} = \gamma_{5,t} = 0$). The second specification is the model of Bakshi et al. (2015) (setting $\gamma_{1,t} = \gamma_{5,t} = \gamma_{6,t} = \gamma_{7,t} = 0$). The third and fourth specification, respectively, add the basis-momentum nearby factor to these models. The fifth model is a two-factor model including the average factor and the basis-momentum nearby factor (setting $\gamma_{2,t} = \gamma_{4,t} = \gamma_{5,t} = \gamma_{6,t} = \gamma_{7,t} = 0$). The motivation for this specification is that the average factor might do a good job capturing the level of commodity returns, whereas the basis-momentum factor might do a good job capturing the cross-sectional variation of commodity returns. The final model tests what the basis-momentum spreading factor adds to this two-factor model.

We perform these cross-sectional regressions using both nearby and spreading returns on the left-hand side. The motivation is that a large share of investors in commodity markets takes positions further down the futures curve, because the horizon of their underlying exposure is not matched by the first-nearby contract or because they desire to hold a spreading position, for instance, to execute a particular roll-over strategy or to hedge out common risk. This approach is similar to using managed portfolios as advocated in Cochrane (2005), but we condition on expiration, not on a lagged instrumental variable.

Furthermore, we consider two sets of test assets. The first set of test assets is a cross section of 32 portfolios that combines the nearby and spreading returns of nine portfolios sorted on basis, momentum, and basis-momentum with seven sector portfolios.[26] For this portfolio-level test, we estimate full sample betas, such that β_t is constant over time. Although adding sector portfolios follows the suggestion in Kan et al. (2013), one might still be concerned that the remaining left-hand side portfolios are constructed from the same sort as the right-hand side factors (Ferson et al. (1999)). To address this concern, the second set of test assets we consider is the cross section of nearby and spreading returns of individual commodities. This approach follows the recent trend in stock markets to perform cross-sectional tests for individual stocks instead of portfolios (see, e.g., Lewellen et al. (2010) and Ang et al. (2011)). This approach is particularly attractive as a check of robustness for the case of

[26]The composition of the sectors (Energy, Meats, Metals, Grains, Oilseeds, Softs, and Industrial Materials) can be found in Table A.1 and follows Szymanowska et al. (2014). Because there are no Energy and Meats commodities in the first years of our sample, these sectors are included only in the sub-sample starting from 1986.

commodities, as the cross section is small to begin with. Therefore, one would like to use as much of the available information as possible, and some information will surely be lost when sorting commodities into portfolios (Daniel and Titman (1997)). In this case, we estimate time-varying commodity level betas over a one year rolling window of daily returns.[27] We switch to a daily frequency to keep the betas timely, which is important because previous literature finds that betas of individual commodities vary quite dramatically over time (Bakshi et al. (2015)). The daily factor returns in month $t+1$ are calculated by combining daily commodity returns in month $t+1$ with portfolio weights at the end of month t. Daskalaki et al. (2014) argue that commodity-level exposures contain lots of noise, making the cross section of individual commodities notoriously hard to price. Therefore, this exercise will present a serious challenge for any new commodity factor.

Table 10 presents the results for portfolios (Panel A) and individual commodities (Panel B). In Panel A, we present annualized risk prices for the factors of interest, their Shanken (1992) t-statistic, and the mean absolute pricing error ($MAPE$). We also decompose the MAPE into the part coming from the sixteen nearby-portfolio returns and the sixteen spreading-portfolio returns ($MAPE^{nearby}$ and $MAPE^{spread}$). In Panel B, we estimate the t-statistics using the procedure of Fama and MacBeth (1973) and the R^2 and $MAPE$'s are from a regression of average commodity return on average beta, to ensure comparability of the cross-sectional fit across panels.

In Panel A, we first see that the three-factor model of Szymanowska et al. (2014) obtains a reasonable cross-sectional fit with an R^2 of 0.65 and a $MAPE$ of 2.18%. The basis nearby factor captures a significant price of risk of -20.75%, which estimate is large economically, but also relative to the average return of this factor: -10.61%. The estimated prices of risk for the two basis spreading return factors are small and insignificant, however. The fit

[27] Estimating rolling window betas automatically deals with the staggered introduction of commodities in the sample. We estimate betas only for those commodities with more than 125 return observations in the window.

improves for the three-factor model of Bakshi et al. (2015) with an R^2 of 0.80 and a $MAPE$ of 1.53%. Further, the estimated prices of risk for all three factors are significant. The third and fourth specification demonstrate that adding the basis-momentum nearby factor to each of these two models improves the cross-sectional fit considerably with R^2's ($MAPE$'s) of 0.79 and 0.92 (1.76% and 1.05%), respectively. The estimated price of risk for the basis-momentum factor is large and significant in both cases at about 18% ($t = 5.8$), which is close to the average return of the basis-momentum factor and translates to a Sharpe ratio of about 0.85. Since none of the benchmark factors is driven out, we conclude that exposures to the basis-momentum factor contain independent information about the cross section of average portfolio returns.

In fact, in the fifth specification we see that a two-factor model, including the average factor and the basis-momentum nearby factor, is comparable to the larger three- and four-factor models in terms of cross-sectional fit, with an R^2 of 0.85 and $MAPE$ of 1.38. In the last model, we see that the basis-momentum spreading factor is significant when added to this two-factor model. However, the improvement in R^2 is only marginal, whereas the $MAPE$ among spreading returns actually increases. This finding suggests that the basis-momentum nearby factor adequately captures the cross-sectional variation in average nearby returns as well as average spreading returns of these portfolios. Although the estimated intercept is negative and significant in models that include the basis-momentum factor, it is small economically at about -1%. We conclude that the two-factor model presents a parsimonious representation of the cross section of average returns, with the average commodity market factor capturing the level of returns and the basis-momentum factor capturing cross-sectional variation.

The pricing evidence for basis-momentum is quantitatively and qualitatively robust in the commodity-level test of Panel B. First, exposure to the basis-momentum factor captures a large and significant price of risk of about 15% (translating to a Sharpe ratio of about 0.55), even when controlling for the benchmark factors. Second, the cross-sectional fit of the parsimonious two-factor model (including the average factor and the basis-momentum factor) is again similar to the larger three- and four-factor models. Among the remaining factors, the basis and average nearby factor are consistently priced, but the momentum nearby factor is not. Similar to the case of portfolios, the basis-momentum spreading factor has little to add in terms of cross-sectional fit. These conclusions are robust when we split the sample in two (see the last four columns of Panels A and B) and when we perform the tests for the larger set of 32 commodities (see Table A.10 of the Internet Appendix).

In sum, the evidence from these cross-sectional asset pricing tests suggests that basis-momentum captures priced risk. The basis-momentum factor is a key determinant of cross-sectional variation in average returns of commodity-sorted portfolios as well as individual commodities, and provides an adequate cross-sectional fit when combined with an average commodity market factor. The larger three- and four-factor models of Szymanowska et al. (2014) and Bakshi et al. (2015) provide a similar fit, with robust prices of risk for the nearby basis and nearby average factor. In contrast, we find little or inconsistent evidence for the pricing of spreading factors as well as the nearby momentum factor.

5.3 The basis-momentum factor and the price of volatility risk

In this subsection we ask whether volatility is a state variable for risk premiums in commodity markets, consistent with the model of Brunnermeier and Pedersen (2009). If the exposure of basis-momentum to volatility risk is economically important, one would expect volatility risk to capture cross-sectional variation in average returns similar to the basis-momentum factor. To this end, we first test whether exposures to volatility risk explain cross-sectional variation in average nearby and spreading returns of commodity-sorted portfolios. We consider two-factor models that include the average commodity market factor and either the aggregate or average commodity market volatility risk factor (instead of the basis-momentum factor). Table 11 presents the results.[28] We find that exposure to volatility risk captures a large and significant negative price of risk, independent of whether this risk is measured as the innovation in aggregate (Δvar_{t+1}^{mkt}) or average (Δvar_{t+1}^{avg}) commodity market variance. The point estimates of -0.08 and -0.24 for the price of volatility risk translate to an annual Sharpe ratio of about -0.65, which is consistent in magnitude with previous evidence in, e.g., Menkhoff et al. (2012a) and Koijen et al. (2015), and also the basis-momentum factor in Table 10. The cross-sectional R^2's in these two models is about 0.65, which is not far below the two-factor model that includes instead of volatility risk the basis-momentum factor or the larger three- and four-factor models. This cross-sectional fit is impressive for a non-traded factor.

Finally, we include both basis-momentum and each volatility factor next to the average commodity market factor. The basis-momentum nearby factor largely drives out the volatility risk factors, leaving only a small and insignificant negative price of volatility risk.We caution to not interpret these regressions as horse races. As noted in Cochrane (2005, Ch. 7), it is pointless to run horse races between models with non-traded factors and return-based mimicking portfolios of these factors. Instead, given that the nearby basis-momentum factor is strongly exposed to volatility risk (see Table 8), we interpret this evidence as supporting the interpretation that basis-momentum is a priced risk factor in commodity markets largely because it mimicks well priced volatility risk.

6 Conclusion

In this paper, we extract a basis-momentum factor related to the slope and curvature of the commodity futures curve and uncover a number of asset pricing implications. These implications are important, because the recent financialization of commodity markets has inspired large and ever-growing institutional investment in commodities.

[28] Table A.11 of the Internet Appendix presents largely similar evidence when the portfolios and right-hand side factors are constructed using the larger cross section of 32 commodities.

Our contribution to the literature follows from three main results. First, basis-momentum is the best known time series and cross-sectional predictor of nearby and spreading returns in commodity markets since their inception in 1959. Second, the basis-momentum effect is maturity-specific, follows from predictability of roll returns (not appreciation of spot commodity prices), and exists also in currency markets. Consequently, basis-momentum is unlikely to be driven by storage or inventory dynamics, but is consistent with maturity-specific (hedger's) price pressure. Consistent with such price pressure, we show that basis-momentum returns are increasing in volatility and exposed to volatility risk. Third, in line with this finding, we find that exposure to a basis-momentum factor is priced, even after controlling for recently developed commodity factor pricing models. A parsimonious two-factor model, including an average commodity market factor and the basis-momentum factor, does a good job explaining cross section variation in nearby and spreading returns. Finally, the basis-momentum effect largely represents a compensation for volatility risk, which we show to be priced much more broadly in commodity markets than was previously known in the literature.

In sum, basis-momentum is key to understanding the variation of commodity prices and thus a crucial input for the models of empiricists, theorists, and practitioners with an interest in commodity markets. Future work is warranted to find the economic drivers of hedger's versus speculator's investment decisions that determine the separate components of basis-momentum: average curvature and changes in the slope of the futures curve, and to better understand why these components jointly are so strongly related to returns relative to benchmark characteristics, such as basis and momentum.

7 Appendix: Currency data

The data for spot as well as one- and two-month forward exchange rates cover the sample period from December 1996 to August 2015, and are obtained from BBI and Reuters (via

Datastream). Although for many currencies spot and one-month forward exchange rates are available before 1996, two-month forward exchange rates are not. Spot and forward rates are observed on the last trading day of a given month. Our total sample consists of the following 48 countries: Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Egypt, Euro area, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Ice- land, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Ukraine, United Kingdom.

We follow Lustig et al. (2013) in cleaning the data. The euro series start in January 1999 and, therefore, we exclude the euro area countries after this date. Some of these currencies have pegged their exchange rate partly or completely to the US dollar over the course of the sample; for this reason, we exclude Hong Kong and Saudi Arabia. Based on large failures of covered interest parity, we deleted the following observations from our sample: Malaysia from the end of August 1998 to the end of June 2005; and Indonesia from the end of December 2000 to the end of May 2007.

In each month t, we sort these currencies in three portfolios. We define currency basis-momentum, basis, and momentum as follows

$$BM^{cur}_{i,t} = \prod_{s=t-2}^{t} (S_{t+1}/F^1_t) - \prod_{s=t-2}^{t} (F^1_{t+1}/F^2_t), \tag{33}$$

$$B^{cur}_{i,t} = F^1_t/S_t - 1, \tag{34}$$

$$M^{cur}_{i,t} = \prod_{s=t-2}^{t} (S_{t+1}/F^1_t) - 1, \tag{35}$$

where S_{t+1}, F^1_{t+1}, and F^2_{t+1} are the spot price and one- and two-month forward price, respectively. Note, we define basis-momentum and momentum using the last three months of returns, because recent evidence on momentum strategies in currency markets shows that performance is superior over shorter ranking periods than twelve months (Menkhoff et al. (2012b)). Basis is calculated as the one month forward price divided by the spot price minus one, which is standard in the currency literature.

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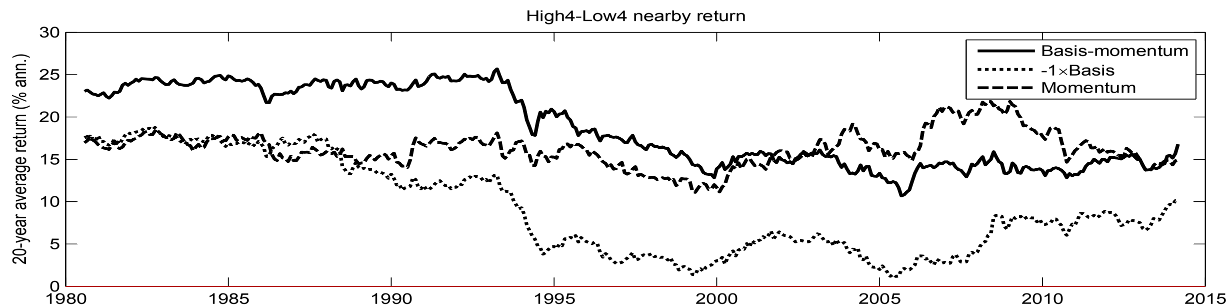

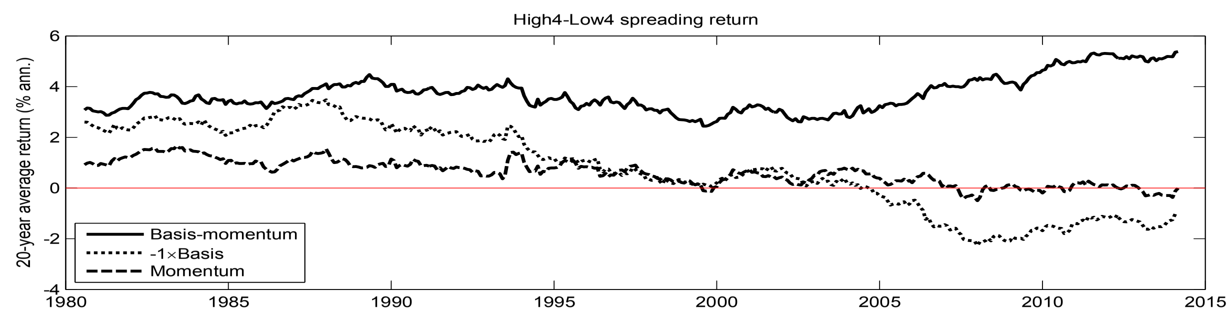

Figure 1: Twenty-year moving average nearby and spreading returns from commodity sorts
This figure presents 20-year moving average nearby (top) and spreading (bottom) returns (annualized %'s) for the basis-momentum, basis, and momentum factors. These factors are constructed as the top (High4) minus bottom (Low4) portfolio from a sort of 21 commodities on each of the respective signals. For the sake of comparison, we present the negative of the returns on the basis strategy. The original sample period is August 1960 to February 2014, such that the first moving average is observed in July 1980.

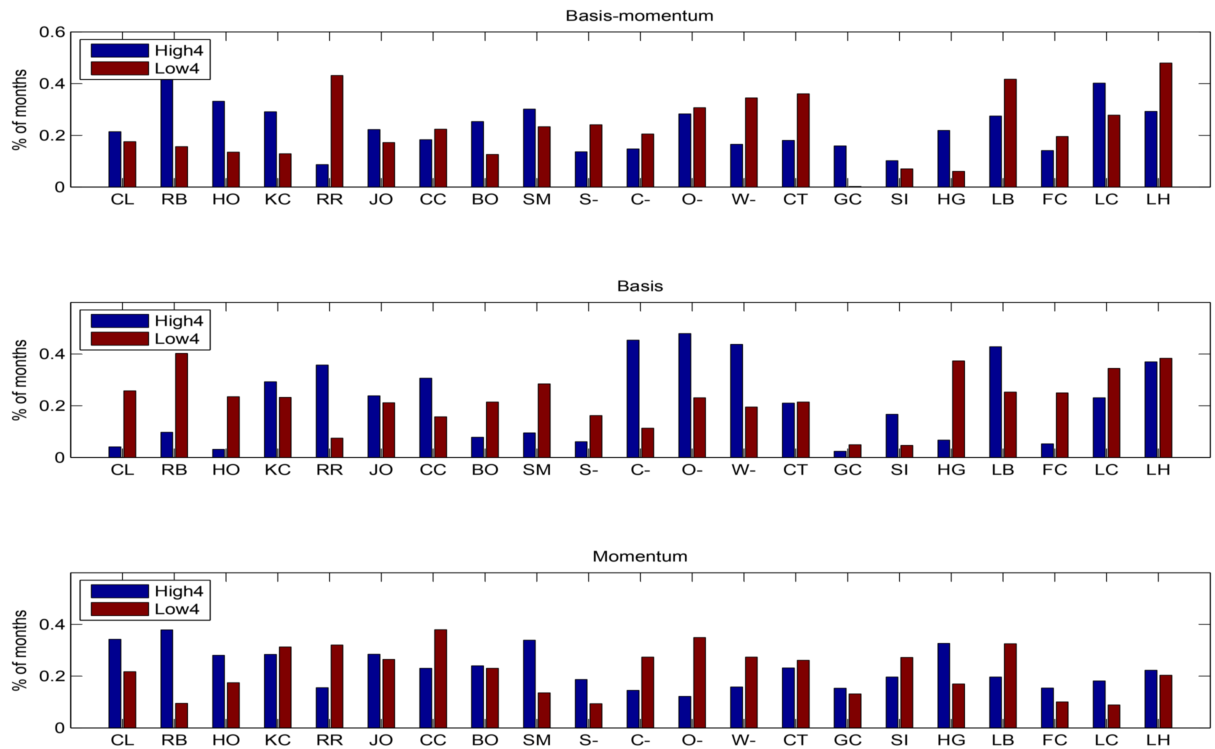

Figure 2: Composition of High4 and Low4 portfolios in commodity sorts
This figure presents the fraction of months in which a given commodity (see symbols in Table A.1) is either among the top four (blue) or bottom four (red) commodities ranked on the three signals of interest: basis-momentum, basis, and momentum. The percentages are calculated as a fraction of the total number of months in which a given commodity is included in the sample. The sample period is August 1960 to February 2014.

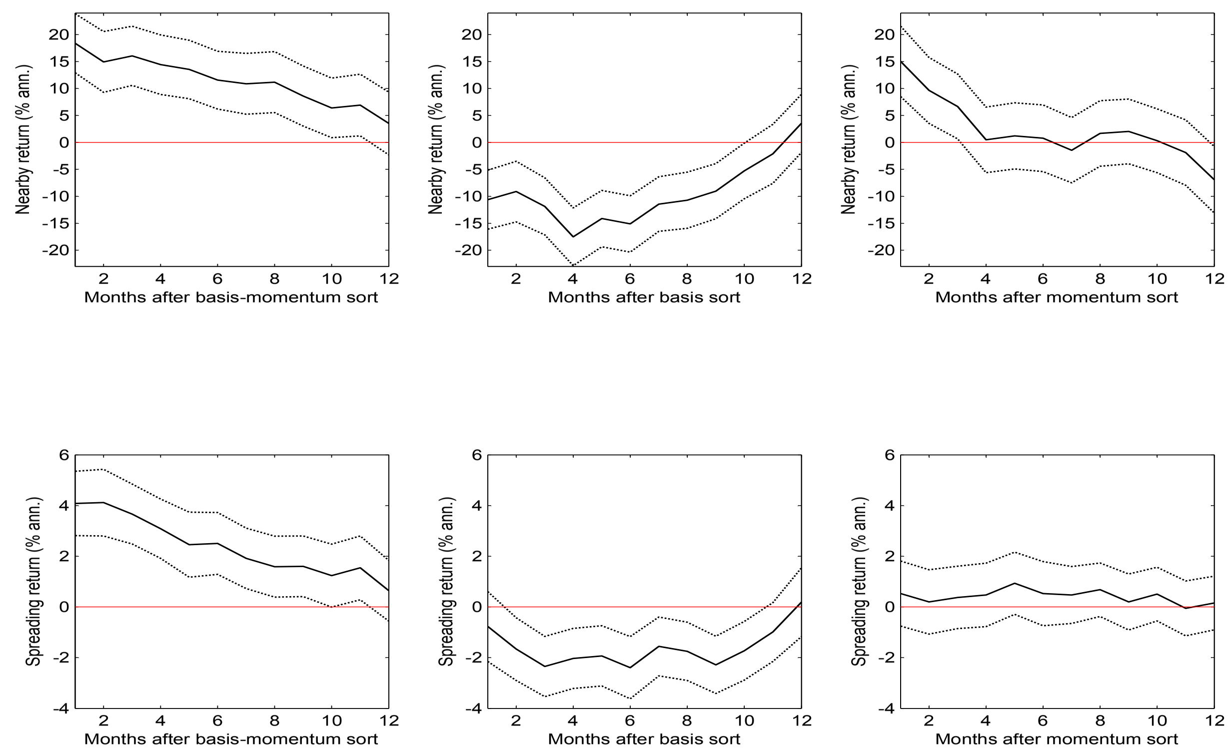

Figure 3: Nearby and spreading returns up to one year after portfolio formation
This figure presents average nearby (top) and spreading (bottom) returns (in annualized %) for the basis-momentum, basis, and momentum factors up to one year after portfolio formation (i.e., with the sort performed at the end of month t we present average returns (plus two standard errors bands) for months $t+1, ..., t+12$). The sample period is August 1960 to February 2014.

Table 1: Commodity portfolios sorted on basis-momentum
This table presents the unconditional performance in both nearby (Panel A) and spreading (Panel B) returns of portfolios sorted on basis-momentum (the difference between momentum signals from first- and second-nearby futures strategies: $\prod_{s=t-11}^{t}(1+R_{fut,s}^{T_1}) - \prod_{s=t-11}^{t}(1+R_{fut,s}^{T_2})$). We also sort commodities on basis ($F_t^{T_2}/F_t^{T_1}-1$) and momentum ($\prod_{s=t-11}^{t}(1+R_{fut,s}^{T_1})$) as a benchmark. The High4 and Low4 portfolio contain the top and bottom four ranked commodities, respectively, whereas the Mid portfolio contains all remaining commodities, which number is time-varying. In each post-ranking month $t+1$, the portfolio's nearby return is the equal-weighted average return of first-nearby contracts, whereas the spreading return is the equal-weighted average of the difference between the return of the first-nearby and second-nearby contract. We present results for the full sample period from August 1960 to February 2014 as well as two sample halves split around January 1986, so that the later sub-sample coincides with Szymanowska et al. (2014).

	Basis-momentum				Basis	Momentum
	High4	Mid	Low4	High4-Low4	High4-Low4	High4-Low4
			Panel A: Nearby returns ($R_{fut,p,t+1}^{T_1}$)			
			Full sample from 1960-08 to 2014-02			
Avg. ret.	15.60	5.02	-2.78	18.38	-10.61	15.02
(t)	(6.35)	(2.49)	(-1.19)	(6.73)	(-3.88)	(4.61)
Sharpe	0.87	0.34	-0.16	0.92	-0.53	0.63
			Sample from 1960-08 to 1986-01			
Avg. ret.	17.85	7.87	-2.31	20.15	-15.62	15.57
(t)	(5.30)	(2.43)	(-0.63)	(5.40)	(-4.43)	(3.79)
Sharpe	1.05	0.48	-0.12	1.07	-0.88	0.75
			Sample from 1986-02 to 2014-02			
Avg. ret.	13.56	2.43	-3.21	16.77	-6.07	14.53
(t)	(3.82)	(0.98)	(-1.09)	(4.23)	(-1.48)	(2.92)
Sharpe	0.72	0.18	-0.21	0.80	-0.28	0.55
			Panel B: Spreading returns ($R_{fut,p,t+1}^{T_1} - R_{fut,p,t+1}^{T_2}$)			
			Full sample from 1960-08 to 2014-02			
Avg. ret.	1.25	-0.06	-2.83	4.08	-0.77	0.53
(t)	(2.54)	(-0.23)	(-6.86)	(6.43)	(-1.13)	(0.82)
Sharpe	0.35	-0.03	-0.94	0.88	-0.15	0.11
			Sample from 1960-08 to 1986-01			
Avg. ret.	2.16	0.41	-0.71	2.88	-1.92	0.72
(t)	(3.08)	(0.98)	(-1.50)	(3.35)	(-1.98)	(0.76)
Sharpe	0.61	0.19	-0.30	0.66	-0.39	0.15
			Sample from 1986-02 to 2014-02			
Avg. ret.	0.42	-0.48	-4.75	5.17	0.27	0.36
(t)	(0.61)	(-2.00)	(-7.42)	(5.60)	(0.28)	(0.41)
Sharpe	0.11	-0.38	-1.40	1.06	0.05	0.08

Table 2: Double sorts on basis-momentum and control variables
This table presents the unconditional performance in both nearby (Panel A) and spreading (Panel B) returns when we double sort commodities in four portfolios (with t-statistics in parentheses). These portfolios are at the intersection of an independent sort into two basis-momentum groups (split at the median) and two control groups. The control groups are formed on the basis (split at a basis of zero), six-month average basis (split at zero), momentum (split at the median), and finally, hedging and spreading pressure (split at the median, see also the definitions in Section 1.4.1). For the sake of comparison, the first two columns present the single sort on each of these variables. The last six columns present the double sort, with the last two columns containing the High-Low basis-momentum return in each control group. In each post-ranking month $t + 1$, the portfolio's nearby return is the equal-weighted average return of first-nearby contracts, whereas the spreading return is the equal-weighted average of the difference between the return of the first-nearby and second-nearby contract. We present results for the full sample period from August 1960 to February 2014 as well as a sample from 1986-02 to 2012-01, dictated by availability of CFTC position data.

Panel A: Average nearby returns ($R^{T_1}_{fut,p,t+1}$)

		Single sort on row variable		Double sort on row variable and basis-momentum					
				High		Low		High-Low	
		Avg. ret.	(t)	Avg. ret.	(t)	Avg. ret.	(t)	Avg. ret.	(t)
Full sample from 1960-08 to 2014-02									
Basis-momentum	High	12.53	(5.98)						
	Low	-1.65	(-0.85)						
	Diff	14.18	(7.73)						
Basis	Contango	1.17	(0.63)	8.00	(3.52)	-2.94	(-1.45)	10.93	(5.06)
	Backward.	12.07	(5.16)	14.87	(5.45)	3.59	(1.31)	11.29	(3.36)
	Diff	-10.90	(-5.28)	-6.88	(-2.46)	-6.52	(-2.38)		
12-Month basis	Contango	1.53	(0.80)	5.95	(2.70)	-2.16	(-1.04)	8.12	(3.71)
	Backwardation	10.23	(4.08)	15.26	(5.35)	2.69	(0.96)	12.57	(3.57)
	Diff	-8.70	(-3.91)	-9.31	(-3.16)	-4.85	(-1.71)		
Momentum	Winners	9.42	(4.33)	14.43	(6.15)	0.82	(0.30)	13.60	(4.86)
	Losers	1.18	(0.62)	9.01	(3.60)	-3.16	(-1.49)	12.18	(4.95)
	Diff	8.24	(4.22)	5.41	(2.10)	3.99	(1.40)		
CFTC data sample from 1986-02 to 2012-01									
Hedging pres.	High	3.02	(1.21)	8.20	(2.31)	-0.42	(-0.16)	8.62	(2.49)
	Low	4.21	(1.47)	12.44	(3.87)	-5.14	(-1.46)	17.58	(5.00)
	Diff	-1.19	(-0.48)	-4.24	(-1.26)	4.72	(1.42)		
Spreading pres.	High	1.80	(0.71)	9.89	(3.03)	-4.65	(-1.61)	14.55	(4.26)
	Low	5.22	(1.83)	10.69	(3.11)	-1.09	(-0.34)	11.78	(3.35)
	Diff	-3.42	(-1.36)	-0.80	(-0.24)	-3.56	(-1.05)		

Table 2 continued

Panel B: Average spreading returns ($R^{T_1}_{fut,p,t+1} - R^{T_2}_{fut,p,t+1}$)

		Single sort on row variable		Double sort on row variable and basis-momentum					
				High		Low		High-Low	
		Avg. ret.	(t)	Avg. ret.	(t)	Avg. ret.	(t)	Avg. ret.	(t)
Full sample from 1960-08 to 2014-02									
Basis-momentum	High	1.15	(3.82)						
	Low	-1.71	(-6.98)						
	Diff	2.87	(7.83)						
Basis	Contango	-0.62	(-3.63)	0.67	(2.64)	-1.45	(-6.44)	2.12	(6.44)
	Backward.	0.06	(0.12)	1.17	(2.07)	-2.34	(-3.68)	3.52	(4.39)
	Diff	-0.67	(-1.41)	-0.50	(-0.84)	0.90	(1.37)		
12-Month basis	Contango	-0.99	(-4.62)	0.61	(1.67)	-1.77	(-6.58)	2.38	(5.46)
	Backwardation	0.79	(1.79)	1.49	(2.71)	-0.96	(-2.03)	2.45	(3.57)
	Diff	-1.78	(-3.77)	-0.88	(-1.40)	-0.81	(-1.52)		
Momentum	Winners	-0.11	(-0.32)	0.93	(2.06)	-1.77	(-3.98)	2.70	(4.63)
	Losers	-0.56	(-2.46)	1.33	(3.20)	-1.72	(-6.36)	3.05	(6.34)
	Diff	0.45	(1.08)	-0.39	(-0.62)	-0.05	(-0.10)		
CFTC data sample from 1986-02 to 2012-01									
Hedging pres.	High	-1.26	(-3.39)	0.27	(0.55)	-2.21	(-4.83)	2.49	(3.85)
	Low	-1.21	(-3.19)	0.25	(0.49)	-2.96	(-5.82)	3.21	(4.76)
	Diff	-0.05	(-0.10)	0.03	(0.04)	0.75	(1.19)		
Spreading pres.	High	-2.29	(-6.12)	-0.12	(-0.23)	-4.05	(-8.35)	3.94	(5.87)
	Low	-0.26	(-0.74)	0.59	(1.21)	-1.29	(-2.72)	1.88	(2.96)
	Diff	-2.03	(-4.31)	-0.71	(-1.08)	-2.77	(-4.54)		

Table 3: Pooled regressions of commodity-level returns on lagged characteristics Panel A and B present results from pooled time series cross-sectional regressions of nearby and spreading returns ($R^{T_1}_{fut,i,t+1}$ in Panel A; $R^{T_1}_{fut,i,t+1} - R^{T_2}_{fut,i,t+1}$ in Panel B) of 21 commodities on lagged characteristics (see Equations (13) and (14)). Model (1) includes only basis-momentum ($BM_{i,t}$) as independent variable. Models (2) and (3) add time fixed effects and commodity fixed effects, respectively. Model (4) adds both fixed effects. Models (5) and (6) substitute basis ($B_{i,t}$) and momentum ($M_{i,t}$), respectively, for basis-momentum. Model (7) includes the three characteristics jointly. We present the estimated coefficients on the characteristics (λ's) as well as the R^2. t-statistics are presented underneath each estimate and are calculated using standard errors clustered in the time dimension. We present results for the full sample period from August 1960 to February 2014 as well as pre- and post-1986 in the last two columns. Panel C presents results for two decompositions of basis-momentum over the full sample period. In the left block of results, we regress futures returns on ($M_{i,t}$) and second-nearby momentum ($M^{T_2}_{i,t}$). In the right block of results we regress futures returns on average curvature and change in slope (see Section 2.3).

	Full sample							Pre-1986	Post-1986
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(7)	(7)
Panel A: Nearby returns ($R^{T_1}_{fut,i,t+1}$)									
λ_{BM}	10.45	9.55	10.25	9.16			9.19	10.63	8.22
(t)	(7.45)	(7.23)	(7.06)	(6.81)			(6.22)	(4.64)	(4.09)
λ_B					-5.89		3.47	5.41	3.64
(t)					(-2.16)		(1.14)	(1.06)	(0.96)
λ_M						1.01	0.33	0.36	0.13
(t)						(2.32)	(0.66)	(0.45)	(0.20)
R^2	0.01	0.18	0.01	0.18	0.18	0.18	0.18	0.22	0.16
Time dummies	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Commodity dummies	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Spreading returns ($R^{T_1}_{fut,i,t+1} - R^{T_2}_{fut,i,t+1}$)									
λ_{BM}	2.34	1.94	2.16	1.71			2.33	1.44	2.75
(t)	(6.89)	(5.63)	(6.30)	(4.89)			(6.71)	(3.27)	(5.10)
λ_B					0.26		0.99	-0.03	1.86
(t)					(0.24)		(0.89)	(-0.02)	(1.21)
λ_M						-0.16	-0.33	-0.33	-0.31
(t)						(-1.22)	(-2.35)	(-1.30)	(-2.45)
R^2	0.02	0.03	0.02	0.03	0.03	0.03	0.04	0.02	0.05
Time dummies	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Commodity dummies	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Decomposing basis-momentum predictability

	$R^{T_1}_{fut,i,t+1}$	$R^{T_1}_{fut,i,t+1} - R^{T_2}_{fut,i,t+1}$		$R^{T_1}_{fut,i,t+1}$	$R^{T_1}_{fut,i,t+1} - R^{T_2}_{fut,i,t+1}$
λ_M	9.06	1.87	λ_{Curv}	6.08	1.64
(t)	(6.65)	(5.67)		(6.24)	(6.07)
$\lambda^{T_2}_M$	-8.84	-2.23	$\lambda_{\Delta Slope}$	8.71	1.26
(t)	(-5.93)	(-6.50)		(2.95)	(1.61)
R^2	0.18	0.04		0.18	0.03
Time dummies	Yes	Yes		Yes	Yes
Commodity dummies	Yes	Yes		Yes	Yes

Table 4: Basis-momentum across the futures curve

This table presents unconditional performance measures from sorting commodities on alternative measures of basis-momentum. We consider the performance of High4-minus-Low4 portfolios in second- and third-nearby futures returns ($R^{T_2}_{fut,s}$ and $R^{T_3}_{fut,s}$) as well as spreading returns between the second- and third-nearby and the third- and fourth-nearby contracts ($R^{T_2}_{fut,s} - R^{T_3}_{fut,s}$ and $R^{T_3}_{fut,s} - R^{T_4}_{fut,s}$). In the first block of results, commodities are sorted on our usual measure of basis-momentum, BM_t. The next two blocks of results sort commodities on basis-momentum measured using farther-from-expiring contracts, denoted $BM^{2,3}_t$ and $BM^{3,4}_t$, respectively. For these sorts, we also present performance statistics using only those months where less than or equal to three (out of eight) commodities in the High4 and Low4 portfolios overlap between BM_t and one of the two alternative measures (denoted, e.g., $BM^{2,3}_t|BM_t$). The sample period is from August 1960 to February 2014.

		Average returns for High4-Low4 portfolio			
		$R^{T_2}_{fut,s}$	$R^{T_2}_{fut,s} - R^{T_3}_{fut,s}$	$R^{T_3}_{fut,s}$	$R^{T_3}_{fut,s} - R^{T_4}_{fut,s}$
BM_t	Avg. Ret.	14.55	2.31	12.42	0.98
	(t)	(5.88)	(4.57)	(5.35)	(2.06)
	Sharpe	0.80	0.63	0.73	0.32
$BM^{2,3}_t$	Avg. Ret.	16.46	2.52		
	(t)	(6.75)	(5.00)		
	Sharpe	0.92	0.68		
$BM^{2,3}_t \vert BM_t$	Avg. Ret.	7.43	1.58		
(231 Months)	(t)	(1.85)	(1.94)		
	Sharpe	0.42	0.44		
$BM^{3,4}_t$	Avg. Ret.			11.96	0.91
	(t)			(4.85)	(1.89)
	Sharpe			0.71	0.28
$BM^{3,4}_t \vert BM_t$	Avg. Ret.			11.52	0.57
(361 Months)	(t)			(3.69)	(0.97)
	Sharpe			0.67	0.18

Table 5: Average spot and roll returns in commodity sorts
This table decomposes average first-nearby futures returns in sorts on basis-momentum in two components: the roll return (coming from rolling over to the second-nearby contract once the first-nearby contract is close to expiration), and the spot return that is calculated by dividing one plus the first-nearby futures return by one plus the first-nearby roll return. The roll return equals zero when the strategy does not roll. We also sort commodities on basis and momentum as a benchmark. The High4 and Low4 portfolios contain the top and bottom four ranked commodities, the Mid portfolio contains the remaining commodities, which number is time-varying. In each post-ranking month $t+1$, returns and their components are calculated as equal-weighted averages across the commodities in a portfolio. The sample period is from August 1960 to February 2014.

	Basis-momentum				Basis	Momentum
	High4	Mid	Low4	High4-Low4	High4-Low4	High4-Low4
Avg. $R^{T_1}_{fut,t+1}$	15.60	5.02	-2.78	18.38	-10.61	15.02
(t)	(6.35)	(2.49)	(-1.19)	(6.73)	(-3.88)	(4.61)
Avg. $R^{spot}_{fut,t+1}$	4.99	9.45	7.82	-2.83	37.92	-7.54
(t)	(1.98)	(4.69)	(3.17)	(-0.98)	(12.88)	(-2.25)
Avg. $R^{roll}_{fut,t+1}$	11.95	-4.08	-9.57	21.53	-48.90	23.05
(t)	(11.54)	(-9.64)	(-13.33)	(17.37)	(-35.03)	(20.15)

Table 6: Time-series predictability of spot and roll returns
This table presents an overview of results from time-series predictive regressions of nearby futures returns, as well as their spot and roll components, on lagged basis-momentum (see Equations (19), (20), (21)). To be precise, we count the number of positive and negative coefficients (η_{BM}, η^{spot}_{BM}, and η^{roll}_{BM}) out of 21 in each of these regressions. Following the approach of Fama and French (1987), the left hand side first-nearby returns are log holding period returns, which equal the sum of the first-nearby roll return at the beginning of the holding period and the spot return of the first-nearby contract over the holding period, i.e., in between two roll dates. As a benchmark, we also present the counts when using as signal $X_{i,t}$ either basis ($B_{i,t}$) or momentum ($M_{i,t}$). We test significance at the 10%-level using White heteroskedasticity-robust standard errors. Note, given that we measure the basis using the price difference of two futures contract it is exactly equal to the negative of the roll return of the first-nearby strategy. For this reason, we omit the test of significance here.

Signal $X_{i,t}$ =	$BM_{i,t}$	$B_{i,t}$	$M_{i,t}$
Panel A: Nearby returns ($r^{T_1}_{fut,i,t+1:t+T_1}$) on $X_{i,t}$			
# $\eta_X > 0$	19	8	14
# $t_{\eta_X} > 1.65$	12	1	4
# $\eta_X \leq 0$	2	13	7
# $t_{\eta_X} \leq -1.65$	0	6	1
Panel B: Spot returns ($r^{spot}_{fut,i,t+1:t+T_1}$) on $X_{i,t}$			
# $\eta^{spot}_X > 0$	10	19	3
# $t_{\eta^{spot}_X} > 1.65$	1	15	0
# $\eta^{spot}_X \leq 0$	11	2	18
# $t_{\eta^{spot}_X} \leq -1.65$	2	0	6
Panel C: Roll returns ($r^{roll}_{fut,i,t+1:t+T_1}$) on $X_{i,t}$			
# $\eta^{roll}_X > 0$	19	0	20
# $t_{\eta^{roll}_X} > 1.65$	18	NA	19
# $\eta^{roll}_X \leq 0$	2	21	1
# $t_{\eta^{roll}_X} \leq -1.65$	0	NA	0

Table 7: Currency portfolios sorted on basis-momentum
This table presents the unconditional performance of currency portfolios sorted on basis-momentum (the difference between momentum signals from one- and two-month currency forward strategies: $\prod_{s=t-2}^{t}(1+S_s/F_{s-1}^1) - \prod_{s=t-2}^{t}(1+F_s^1/F_{s-1}^2)$). We also sort currencies on basis ($F_t^1/S_t - 1$) and momentum ($\prod_{s=t-2}^{t}(1+S_s/F_{s-1}^1)$) as a benchmark. The portfolios are equal-weighted and contain a subset of a total of 48 currencies with spot as well as one- and two-month forward prices available in Datastream. Nearby (Panel A) and spreading (Panel B) returns are defined as: $r_{cur,t+1}^1 = S_{t+1}/F_t^1$ (the return from buying a currency at the one month forward price) and $r_{cur,t+1}^{spread} = r_{cur,t+1}^1 - F_{t+1}^1/F_t^2$ (which subtracts from the nearby return the return from closing a two-month currency forward contract one month after initiation). The High4 and Low4 portfolio contain the top and bottom four ranked currencies, respectively, whereas the Mid portfolio contains all remaining currencies, which number is time-varying. We present results for the sample period from April 1997 to August 2015, dictated by data availability.

	Basis-momentum				Basis	Momentum
	High4	Mid	Low4	High4-Low4	High4-Low4	High4-Low4
Panel A: Nearby currency forward returns ($r_{cur,t+1}^1$)						
Avg. Ret.	6.22	1.35	-1.84	8.06	-9.99	6.78
(t)	(2.78)	(0.75)	(-0.83)	(3.47)	(-4.45)	(2.49)
Sharpe	0.65	0.18	-0.19	0.81	-1.04	0.58
Panel B: Spreading currency forward returns ($r_{cur,t+1}^{spread}$)						
Avg. Ret.	0.53	0.09	-0.25	0.78	-1.03	0.13
(t)	(2.07)	(2.64)	(-1.10)	(2.32)	(-3.17)	(0.56)
Sharpe	0.48	0.62	-0.26	0.54	-0.74	0.13

Table 8: Volatility and basis-momentum portfolios

This table presents the result from two tests that link basis-momentum-sorted portfolios to volatility. Aggregate commodity market variance, var_t^{mkt}, is calculated as the sum of squared daily returns on an equal-weighted commodity index, and average commodity market variance, var_t^{avg}, is calculated as the equal weighted average of the sum of squared daily returns of individual commodities. Both variance series are winsorized at the 1%-level and standardized to accommodate interpretation. Panel A presents coefficient estimates, v_{var}, from time series regressions of basis-momentum (nearby and spreading) portfolio returns (compounded over horizons of $k = 1, 6, 12$ months) on lagged variance. Panel B presents coefficient estimates, nu_{var}, from time series regressions of nearby and spreading returns on contemporaneous monthly innovations in the variance series. To conserve space, we present only the estimated coefficient, v_1, with its t-statistic computed using Newey-West standard errors with k lags. The sample period is August 1960 to February 2014.

Panel A: Does volatility predict basis-momentum portfolio returns?

	Nearby returns ($R^{T_1}_{fut,p,t+1:t+k}$)						Spreading returns ($R^{T_1}_{fut,p,t+1:t+k} - R^{T_2}_{fut,p,t+1:t+k}$)					
k	1				6	12	1				6	12
	High4	Mid	Low4	High4-Low4	High4-Low4	High4-Low4	High4	Mid	Low4	High4-Low4	High4-Low4	High4-Low4
v_{var}^{mkt}	2.25	-1.02	-5.31	7.56	7.25	5.78	-0.39	-0.41	-1.24	0.85	1.20	1.27
(t)	(0.52)	(-0.27)	(-1.42)	(1.85)	(2.13)	(1.91)	(-0.86)	(-1.16)	(-2.73)	(1.16)	(1.74)	(3.02)
R^2	0.00	0.00	0.01	0.01	0.05	0.05	0.00	0.00	0.01	0.00	0.02	0.04
v_{var}^{avg}	2.05	-2.03	-5.04	7.09	5.64	4.60	-0.66	-0.37	-1.58	0.92	1.37	1.53
(t)	(0.60)	(-0.66)	(-1.39)	(1.94)	(1.81)	(1.59)	(-1.32)	(-0.99)	(-3.89)	(1.33)	(2.18)	(3.59)
R^2	0.00	0.00	0.01	0.01	0.03	0.03	0.00	0.00	0.02	0.00	0.03	0.07

Panel B: Are basis-momentum portfolios exposed to volatility risk?

	Nearby returns ($R^{T_1}_{fut,p,t+1}$)				Spreading returns ($R^{T_1}_{fut,p,t+1} - R^{T_2}_{fut,p,t+1}$)			
	High4	Mid	Low4	High4-Low4	High4	Mid	Low4	High4-Low4
ν_{var}^{mkt}	-7.78	-2.13	0.87	-8.65	-0.18	-0.57	-0.14	-0.03
(t)	(-1.83)	(-0.54)	(0.19)	(-3.14)	(-0.46)	(-2.56)	(-0.35)	(-0.05)
ν_{var}^{avg}	-1.68	-0.12	1.14	-2.82	-0.02	-0.10	0.14	-0.16
(t)	(-1.12)	(-0.10)	(0.84)	(-2.63)	(-0.11)	(-1.12)	(0.78)	(-0.62)

Table 9: Basis-momentum factors versus benchmark commodity factors
Panel A of this table presents summary statistics for the basis-momentum nearby and spreading factors, which are constructed as the nearby ($R^{nearby}_{BM,t+1}$) and spreading ($R^{spread}_{BM,t+1}$) return of the High4-minus-Low4 portfolio from univariate sorts of 21 commodities (see Table 1). To benchmark these new factors, we also present summary statistics for the factors in two recently developed commodity pricing models. The first model (1) of Szymanowska et al. (2014) contains three factors, which are all constructed from a sort on the basis: (i) the nearby return for the High4-minus-Low4 basis portfolio ($R^{nearby}_{B,t+1}$), (ii) the spreading return of the High4 basis portfolio ($R^{spread}_{B,High4,t+1}$), and (iii) the spreading return of the Low4 basis portfolio ($R^{spread}_{B,Low4,t+1}$). The second model (2) of Bakshi et al. (2015) contains three nearby return factors: (i) a market index ("the average factor", $R^{nearby}_{AVG,t+1}$), (ii) the nearby return for the High4-minus-Low4 basis portfolio (as in the model of de Szymanowska et al. (2014)), and (iii) the nearby return for the High4-minus-Low4 momentum portfolio ($R^{nearby}_{M,t+1}$). Panel B presents spanning tests that ask whether the basis-momentum factors provide an abnormal return over these two benchmark models. We present results for the full sample period from August 1960 to February 2014. The last two columns of Panel B summarize the spanning regressions for two subsamples, split around January 1986. t-statistics are presented underneath each estimate and are calculated using Newey-West standard errors with lag length one.

Panel A: Summary statistics

	Avg. ret.	St.Dev.	Skew.	Kurt.	AR(1)	Correlations $R^{nearby}_{BM,t+1}$	$R^{nearby}_{B,t+1}$,	$R^{nearby}_{AVG,t+1}$	$R^{nearby}_{M,t+1}$	$R^{spread}_{BM,t+1}$	$R^{spread}_{B,High4,t+1}$
$R^{nearby}_{BM,t+1}$	18.38	19.99	0.24	5.15	0.09						
$R^{nearby}_{B,t+1}$ (1),(2)	-10.61	20.01	0.28	6.60	0.04	-0.43					
$R^{nearby}_{AVG,t+1}$ (2)	5.00	12.96	0.31	7.90	0.03	0.04	-0.06				
$R^{nearby}_{M,t+1}$ (2)	15.02	23.85	0.07	4.35	0.07	0.27	-0.38	0.10			
$R^{spread}_{BM,t+1}$	4.08	4.65	0.17	5.54	0.05	0.50	-0.26	-0.01	0.17		
$R^{spread}_{B,High4,t+1}$ (1)	-1.11	2.50	0.23	5.55	0.11	-0.19	0.36	0.14	-0.15	-0.29	
$R^{spread}_{B,Low4,t+1}$ (1)	-0.34	4.39	-0.90	11.38	0.05	0.18	-0.36	0.01	0.12	0.32	0.01

Panel B: Spanning regressions

	Full sample α_{BM}	β^{nearby}_{B}	$\beta^{spread}_{B,High4}$	$\beta^{spread}_{B,Low4}$	β^{nearby}_{AVG}	β^{nearby}_{M}	R^2	Pre-1986 α_{BM}	Post-1986 α_{BM}
Basis-momentum nearby factor									
$R^{nearby}_{BM,t+1}$	13.82	-0.39	-0.43	0.19			0.18	11.93	14.10
	(5.46)	(-6.62)	(-1.31)	(1.04)				(3.40)	(3.72)
$R^{nearby}_{BM,t+1}$	12.76	-0.38			0.01	0.11	0.19	12.49	12.46
	(5.09)	(-6.29)			(0.06)	(2.16)		(3.51)	(3.65)
Basis-momentum spreading factor									
$R^{spread}_{BM,t+1}$	3.49	-0.01	-0.52	0.32			0.19	1.49	4.50
	(6.11)	(-1.29)	(-6.77)	(5.26)				(2.05)	(5.43)
$R^{spread}_{BM,t+1}$	3.32	-0.05			-0.01	0.02	0.07	1.65	4.61
	(5.35)	(-5.73)			(-0.60)	(1.80)		(1.96)	(5.19)

Table 10: Cross-sectional asset pricing tests for commodity factor models

This table presents cross-sectional asset pricing tests for six candidate commodity factor models. The first model of Szymanowska et al. (2014) contains the basis nearby factor ($R^{nearby}_{B,t+1}$) as well as the spreading return of both the High4 and Low4 basis portfolio ($R^{spread}_{B,High4,t+1}$ and $R^{spread}_{B,Low4,t+1}$). The second model of Bakshi et al. (2015) contains three nearby factors: a market index ("the average factor", $R^{nearby}_{AVG,t+1}$), a basis factor ($R^{nearby}_{B,t+1}$), and a momentum factor ($R^{nearby}_{M,t+1}$). The third and fourth model add the basis-momentum nearby factor ($R^{nearby}_{BM,t+1}$) to these two models. The fifth model is a two-factor model including the average commodity market index and the basis-momentum nearby factor. The sixth model adds the basis-momentum spreading factor to this specification ($R^{spread}_{BM,t+1}$). The portfolio-level test in Panel A regresses the average returns of 32 commodity-sorted portfolios (that is, the nearby and spreading return of 9 portfolios sorted on basis-momentum, basis, and momentum (the High4, Mid, and Low4 portfolio from each of these sorts) and 7 sector portfolios (Energy, Grains, Industrial Materials, Meats, Metals, Oilseeds, and Softs)) on their full sample exposures. The commodity-level test in Panel B conducts monthly Fama and MacBeth (1973) cross-sectional regressions of the nearby and spreading returns of 21 commodities on their historical exposure, estimated over a one year rolling window of daily returns. Due to the staggered introduction of commodities in the sample, the size of the cross-section is also time-varying. We present the estimated prices of risk (γ) with corresponding t-statistics in parentheses underneath each estimate (the standard errors are calculated following Shanken (1992) in Panel A and Fama and MacBeth (1973) in Panel B). Also, we present the cross-sectional R^2 and the mean absolute pricing error ($MAPE$, in brackets), which is further decomposed in the $MAPE$ among nearby returns and spreading returns. These measures follow from a regression of average returns on full sample betas in Panel A and average returns on average betas in Panel B. We present results for the full sample period from August 1960 to February 2014, but also summarize the evidence for two subsamples, split around January 1986, focusing on the price of risk for the nearby basis-momentum factor and cross-sectional fit.

Table 10 continued

	Full sample									Pre- versus post-1986			
	γ_0	γ_{BM}^{nearby}	γ_B^{nearby}	γ_{AVG}^{nearby}	γ_M^{nearby}	γ_{BM}^{spread}	$\gamma_{B,High4}^{spread}$	$\gamma_{B,Low4}^{spread}$	R^2 $MAPE$	$MAPE_{nearby}$ $MAPE_{spread}$	γ_{BM}^{nearby}	R^2 $MAPE$	γ_{BM}^{nearby}	R^2 $MAPE$
Panel A: Portfolio-level test with full sample betas														
Model 1	0.42		-20.75				1.32	-1.94	0.65	[3.04]		0.69		0.56
	(0.66)		(-6.38)				(1.02)	(-1.15)	[2.18]	[1.33]		[2.39]		[2.40]
Model 2	-0.78		-15.81	5.27	15.79				0.80	[2.27]		0.75		0.75
	(-2.94)		(-5.49)	(2.90)	(4.76)				[1.53]	[0.78]		[1.84]		[1.88]
Model 3	0.23	18.20	-16.86				1.61	-2.28	0.79	[2.25]	17.76	0.80	19.69	0.72
	(0.37)	(5.78)	(-5.22)				(1.22)	(-1.34)	[1.76]	[1.27]	(3.76)	[1.96]	(4.16)	[1.90]
Model 4	-0.88	17.86	-12.60	5.35	15.13				0.92	[1.38]	21.72	0.91	16.17	0.81
	(-3.36)	(5.79)	(-4.42)	(2.95)	(4.55)				[1.05]	[0.73]	(4.88)	[1.17]	(3.76)	[1.61]
Model 5	-0.98	21.11		5.56					0.85	[2.08]	23.87	0.88	20.18	0.73
	(-3.65)	(6.71)		(3.06)					[1.38]	[0.67]	(5.57)	[1.30]	(4.17)	[1.85]
Model 6	-1.08	20.42		5.55		6.34			0.87	[1.71]	22.90	0.89	20.26	0.74
	(-3.71)	(6.41)		(3.05)		(3.82)			[1.30]	[0.89]	(5.36)	[1.40]	(4.26)	[1.82]
Panel B: Commodity-level test with historical betas														
Model 1	1.36		-15.76				0.86	1.25	0.55	[2.78]		0.20		0.63
	(1.87)		(-3.92)				(0.70)	(0.79)	[2.28]	[1.78]		[3.45]		[2.12]
Model 2	-0.03		-17.73	4.43	-1.53				0.80	[2.04]		0.44		0.79
	(-0.08)		(-4.02)	(2.42)	(-0.34)				[1.53]	[1.03]		[2.60]		[1.79]
Model 3	1.41	15.94	-14.05				0.35	-0.09	0.54	[2.74]	11.68	0.23	19.58	0.70
	(2.12)	(4.05)	(-3.31)				(0.29)	(-0.06)	[2.25]	[1.77]	[2.10]	[3.25]	[3.51]	[2.04]
Model 4	-0.05	15.99	-15.87	4.50	-0.25				0.82	[1.84]	10.43	0.45	21.32	0.80
	(-0.14)	(3.99)	(-3.43)	(2.49)	(-0.05)				[1.41]	[0.99]	[1.87]	[2.53]	[3.75]	[1.75]
Model 5	0.10	14.79		4.22					0.74	[2.69]	13.84	0.36	15.67	0.68
	(0.23)	(4.00)		(2.32)					[1.80]	[0.91]	[2.73]	[2.88]	[2.94]	[2.13]
Model 6	0.37	16.01		3.92		2.35			0.78	[2.51]	15.23	0.42	16.89	0.70
	(0.90)	(4.36)		(2.17)		(1.64)			[1.55]	[0.60]	[2.99]	[2.63]	[3.21]	[1.95]

Table 11: Cross-sectional asset pricing tests: Basis-momentum versus volatility risk

This table conducts portfolio-level cross-sectional regressions to test the relation between the pricing of basis-momentum and volatility risk. We consider five models. The first model contains the average nearby factor ($R^{nearby}_{AVG,t+1}$) as well as the basis-momentum nearby factor ($R^{nearby}_{BM,t+1}$). The second and third model replace the basis-momentum factor with non-traded innovations in aggregate and average commodity market variance, respectively, i.e., Δvar^{mkt}_{t+1} and Δvar^{avg}_{t+1}. In models four and five, we include both basis-momentum and the volatility risk factors. We regress the average returns of 32 commodity-sorted portfolios (that is, the nearby and spreading return of 9 portfolios sorted on basis-momentum, basis, and momentum (the High4, Mid, and Low4 portfolio from these sorts) and 7 sector portfolios (Energy, Grains, Industrial Materials, Meats, Metals, Oilseeds, and Softs)) on their full sample exposures. We present the estimated prices of risk (γ) with corresponding Shanken (1992) t-statistics in parentheses underneath each estimate. Also, we present the cross-sectional R^2 and the mean absolute pricing error ($MAPE$, in brackets), which is further decomposed in the $MAPE$ among nearby returns and spreading returns. We present results for the full sample period from August 1960 to February 2014.

	γ_0	γ^{nearby}_{AVG}	γ^{nearby}_{BM}	γ^{mkt}_{var}	γ^{avg}_{var}	R^2 / $MAPE$	$MAPE_{nearby}$ / $MAPE_{spread}$
Model 1	-0.98	5.56	21.11			0.85	[2.08]
	(-3.65)	(3.06)	(6.71)			[1.38]	[0.67]
Model 2	-1.41	6.60		-0.08		0.64	[3.27]
	(-4.37)	(3.58)		(-3.57)		[2.12]	[0.98]
Model 3	-1.11	6.48			-0.24	0.65	[3.13]
	(-3.09)	(3.49)			(-3.38)	[2.03]	[0.93]
Model 4	-1.06	5.75	20.60	-0.02		0.85	[1.99]
	(-4.04)	(3.17)	(6.80)	(-0.80)		[1.34]	[0.69]
Model 5	-1.04	5.85	20.45		-0.08	0.86	[1.90]
	(-3.83)	(3.21)	(6.55)		(-1.21)	[1.29]	[0.68]

Internet Appendix

This Internet Appendix presents additional empirical evidence. A number of these tables are identical to one in the paper, albeit using a larger sample of 32 commodities. The exceptions are Tables A.5 and A.7, which provide additional evidence from time series predictive regressions for individual commodities, and Table A.8 which relates basis and momentum returns to volatility.

Table A.1: Overview of commodity futures contracts

This table presents the sample of returns of first- and second-nearby futures strategies ($R^{T_1}_{fut,t+1}$ and $R^{T_2}_{fut,t+1}$) for 32 commodity futures, divided over seven sectors: Energy, Grains, Industrial Material, Meats, Metals, Oilseeds, and Softs. The table lists for each commodity: sector, symbol, whether it belongs to the smaller sample of Szymanowska et al. (2014), the first observation of a return on the second-nearby contract, as well as average return and standard deviation for both contracts.

			In small		$R^{T_1}_{fut,t+1}$		$R^{T_1}_{fut,t+1}$	
Name	Sector	Mnemonic	sample?	First obs.	Avg. ret.	St. dev.	Avg. ret.	St. dev.
Crude Oil	Energy	CL	Y	198304	11.68	32.83	11.99	30.77
Gasoline	Energy	HU/RB	Y	198501	18.18	34.57	16.03	31.28
Heating Oil	Energy	HO	Y	197904	9.63	30.98	8.61	29.38
Natural Gas	Energy	NG	N	199005	-5.18	49.62	-0.20	42.44
Gas-Oil-Petroleum	Energy	LF	N	198909	13.35	30.69	12.53	29.02
Propane	Energy	PN	N	198710	23.38	46.89	20.41	39.31
Rough Rice	Grains	RR	Y	198609	-3.54	27.68	1.20	26.04
Sugar	Grains	SB	N	196102	6.54	42.82	8.02	39.01
Corn	Grains	C-	Y	195908	-1.28	23.92	0.07	23.05
Oats	Grains	O-	Y	195908	0.24	29.28	0.28	26.91
Wheat	Grains	W-	Y	195908	-0.87	24.80	0.80	23.90
Canola	Grains	WC	N	197702	-0.38	21.99	0.87	20.58
Barley	Grains	WA	N	198906	-1.16	22.01	1.78	22.05
Cotton	Ind. Mat.	CT	Y	195908	2.40	23.68	3.96	22.10
Lumber	Ind. Mat.	LB	Y	196911	-4.11	27.37	-1.72	23.27
Rubber	Ind. Mat.	YR	N	199202	4.61	32.74	3.45	31.48
Feeder Cattle	Meats	FC	Y	197112	3.69	16.24	5.35	15.58
Live Cattle	Meats	LC	Y	196412	5.02	16.21	4.66	14.19
Lean Hogs	Meats	LH	Y	196603	4.36	25.13	7.74	22.53
Pork Bellies	Meats	PB	N	196204	2.88	33.27	4.78	30.91
Gold	Metals	GC	Y	197501	1.50	19.58	1.45	19.63
Silver	Metals	SI	Y	196307	4.26	31.35	4.47	31.32
Copper	Metals	HG	Y	195908	11.66	26.79	10.61	25.36
Palladium	Metals	PA	N	197702	12.08	35.12	13.04	33.70
Platinum	Metals	PL	N	196902	5.22	27.56	5.12	27.66
Soybean Oil	Oilseeds	BO	Y	195908	6.65	29.33	6.14	28.05
Soybean Meal	Oilseeds	SM	Y	195908	9.91	29.02	10.24	28.03
Soybeans	Oilseeds	S-	Y	195908	6.04	25.86	7.36	25.60
Coffee	Softs	KC	Y	197209	6.68	37.68	5.17	35.47
Orange Juice	Softs	JO	Y	196703	5.53	32.79	5.28	31.54
Cocoa	Softs	CC	Y	195908	3.40	30.86	3.23	29.28
Milk	Softs	DE	N	199602	5.67	23.91	6.08	18.02

Table A.2: Commodity portfolios sorted on basis-momentum (32 commodities) This table is similar to Table 1 in the paper, but uses the larger cross-section of 32 commodities. This table presents the unconditional performance in both nearby (Panel A) and spreading (Panel B) returns of portfolios sorted on basis-momentum (the difference between momentum signals from first- and second-nearby futures strategies: $\prod_{s=t-11}^{t}(1+R_{fut,s}^{T_1}) - \prod_{s=t-11}^{t}(1+R_{fut,s}^{T_2})$). We also sort commodities on basis ($F_t^{T_2}/F_t^{T_1} - 1$) and momentum ($\prod_{s=t-11}^{t}(1+R_{fut,s}^{T_1})$) as a benchmark. The High4 and Low4 portfolio contain the top and bottom four ranked commodities, respectively, whereas the Mid portfolio contains all remaining commodities, which number is time-varying. In each post-ranking month $t+1$, the portfolio's nearby return is the equal-weighted average return of first-nearby contracts, whereas the spreading return is the equal-weighted average of the difference between the return of the first-nearby and second-nearby contract. We present results for the full sample period from August 1960 to February 2014 as well as two sample halves split around January 1986, so that the later sub-sample coincides with Szymanowska et al. (2014).

	Basis-momentum				Basis	Momentum
	High4	Mid	Low4	High4-Low4	High4-Low4	High4-Low4
Panel A: Nearby returns ($R_{fut,p,t+1}^{T_1}$)						
Full sample from 1960-08 to 2014-02						
Avg. ret.	20.46	4.12	-1.63	22.09	-7.68	18.65
(t)	(7.42)	(2.12)	(-0.63)	(6.98)	(-2.52)	(5.01)
Sharpe	1.01	0.29	-0.09	0.95	-0.34	0.68
Sample from 1960-08 to 1986-01						
Avg. ret.	20.75	6.19	-3.14	23.89	-13.16	20.07
(t)	(5.61)	(1.99)	(-0.78)	(5.81)	(-3.13)	(3.98)
Sharpe	1.11	0.39	-0.15	1.15	-0.62	0.79
Sample from 1986-02 to 2014-02						
Avg. ret.	20.20	2.24	-0.25	20.45	-2.71	17.35
(t)	(4.98)	(0.93)	(-0.08)	(4.30)	(-0.62)	(3.19)
Sharpe	0.94	0.18	-0.01	0.81	-0.12	0.60
Panel B: Spreading returns ($R_{fut,p,t+1}^{T_1} - R_{fut,p,t+1}^{T_2}$)						
Full sample from 1960-08 to 2014-02						
Avg. ret.	1.71	-0.22	-3.33	5.04	-0.55	0.03
(t)	(2.80)	(-1.05)	(-6.57)	(6.40)	(-0.66)	(0.03)
Sharpe	0.38	-0.14	-0.90	0.87	-0.09	0.00
Sample from 1960-08 to 1986-01						
Avg. ret.	1.75	0.13	-1.17	2.92	-1.48	1.01
(t)	(2.40)	(0.37)	(-1.79)	(3.04)	(-1.43)	(0.98)
Sharpe	0.47	0.07	-0.35	0.60	-0.28	0.19
Sample from 1986-02 to 2014-02						
Avg. ret.	1.68	-0.53	-5.28	6.96	0.30	-0.87
(t)	(1.74)	(-2.20)	(-7.08)	(5.73)	(0.23)	(-0.79)
Sharpe	0.33	-0.42	-1.34	1.08	0.04	-0.15

Table A.3: Double sorts on basis-momentum and control variables (32 commodities)

This table is similar to Table 2 in the paper, but uses the larger cross-section of 32 commodities. This table presents the unconditional performance in both nearby (Panel A) and spreading (Panel B) returns when we double sort commodities in four portfolios (with t-statistics in parentheses). These portfolios are at the intersection of an independent sort into two basis-momentum groups (split at the median) and two control groups. The control groups are formed on the basis (split at a basis of zero), six-month average basis (split at zero), momentum (split at the median), and finally, hedging and spreading pressure (split at the median, see also the definitions in Section 1.4.1). For the sake of comparison, the first two columns present the single sort on each of these variables. The last six columns present the double sort, with the last two columns containing the High-Low basis-momentum return in each control group. In each post-ranking month $t+1$, the portfolio's nearby return is the equal-weighted average return of first-nearby contracts, whereas the spreading return is the equal-weighted average of the difference between the return of the first-nearby and second-nearby contract. We present results for the full sample period from August 1960 to February 2014 as well as a sample from 1986-02 to 2012-01, dictated by availability of CFTC position data.

Panel A: Average nearby returns ($R^{T_1}_{fut,p,t+1}$)

		Single sort on row variable		Double sort on row variable and basis-momentum					
				High		Low		High-Low	
		Avg. ret.	(t)	Avg. ret.	(t)	Avg. ret.	(t)	Avg. ret.	(t)
Full sample from 1960-08 to 2014-02									
Basis-momentum	High	13.22	(6.22)						
	Low	-2.00	(-1.01)						
	Diff	15.22	(8.32)						
Basis	Contango	1.80	(0.94)	8.84	(3.91)	-2.98	(-1.45)	11.82	(5.69)
	Backward.	11.49	(4.96)	17.70	(6.79)	1.43	(0.49)	16.27	(4.98)
	Diff	-9.69	(-4.71)	-8.85	(-3.34)	-4.41	(-1.56)		
12-Month basis	Contango	2.47	(1.25)	9.10	(3.59)	-2.14	(-1.01)	11.24	(4.63)
	Backwardation	9.48	(4.02)	16.03	(5.94)	-1.38	(-0.46)	17.40	(5.27)
	Diff	-7.01	(-3.28)	-6.93	(-2.38)	-0.76	(-0.26)		
Momentum	Winners	11.30	(5.01)	17.20	(6.97)	1.60	(0.58)	15.60	(5.81)
	Losers	-0.12	(-0.06)	5.27	(2.18)	-3.66	(-1.74)	8.93	(3.73)
	Diff	11.42	(5.71)	11.93	(4.57)	5.26	(1.91)		
CFTC data sample from 1986-02 to 2012-01									
Hedging pres.	High	3.46	(1.38)	10.38	(3.09)	-1.59	(-0.60)	11.97	(3.54)
	Low	5.10	(1.82)	12.74	(3.75)	-3.94	(-1.17)	16.68	(4.54)
	Diff	-1.63	(-0.66)	-2.36	(-0.68)	2.35	(0.72)		
Spreading pres.	High	1.62	(0.64)	9.53	(2.94)	-4.51	(-1.56)	14.04	(4.29)
	Low	6.87	(2.49)	13.50	(3.85)	1.24	(0.37)	12.27	(3.20)
	Diff	-5.25	(-2.15)	-3.97	(-1.19)	-5.74	(-1.68)		

Table A.3 continued

Panel B: Average spreading returns ($R^{T_1}_{fut,p,t+1} - R^{T_2}_{fut,p,t+1}$)

		Single sort on row variable		Double sort on row variable and basis-momentum					
				High		Low		High-Low	
		Avg. ret.	(t)	Avg. ret.	(t)	Avg. ret.	(t)	Avg. ret.	(t)
		Full sample from 1960-08 to 2014-02							
Basis-momentum	High	1.15	(3.79)						
	Low	-1.82	(-7.15)						
	Diff	2.97	(7.89)						
Basis	Contango	-0.60	(-3.29)	0.73	(3.18)	-1.56	(-5.86)	2.29	(6.70)
	Backward.	-0.19	(-0.42)	1.46	(2.58)	-2.89	(-4.77)	4.35	(5.44)
	Diff	-0.42	(-0.89)	-0.73	(-1.24)	1.33	(2.05)		
12-Month basis	Contango	-0.82	(-3.68)	0.90	(2.21)	-1.91	(-6.48)	2.81	(5.76)
	Backwardation	0.56	(1.35)	1.60	(3.11)	-1.60	(-3.25)	3.20	(4.67)
	Diff	-1.38	(-3.02)	-0.71	(-1.14)	-0.32	(-0.56)		
Momentum	Winners	-0.05	(-0.14)	1.35	(2.97)	-1.98	(-4.88)	3.33	(5.74)
	Losers	-0.66	(-2.83)	1.11	(2.99)	-1.72	(-5.68)	2.83	(6.02)
	Diff	0.62	(1.58)	0.25	(0.42)	-0.26	(-0.54)		
		CFTC data sample from 1986-02 to 2012-01							
Hedging pres.	High	-0.96	(-2.35)	0.85	(1.39)	-2.08	(-4.24)	2.93	(3.79)
	Low	-1.19	(-3.18)	0.83	(1.38)	-3.42	(-6.40)	4.25	(5.44)
	Diff	0.22	(0.45)	0.02	(0.02)	1.34	(1.97)		
Spreading pres.	High	-2.15	(-5.56)	-0.24	(-0.42)	-3.79	(-7.60)	3.54	(4.84)
	Low	-0.07	(-0.17)	1.50	(2.33)	-1.47	(-2.63)	2.97	(3.53)
	Diff	-2.08	(-4.13)	-1.74	(-2.17)	-2.31	(-3.29)		

Table A.4: Pooled regressions of commodity-level returns on lagged characteristics (32 commodities)

This table is similar to Table 3 in the paper, but uses the larger cross-section of 32 commodities. Panel A and B present results from pooled time series cross-sectional regressions of nearby and spreading futures returns ($R^{T_1}_{fut,i,t+1}$ in Panel A; $R^{T_1}_{fut,i,t+1} - R^{T_2}_{fut,i,t+1}$ in Panel B) of 32 commodities on lagged characteristics (see Equations (13) and (14)). Model (1) includes only basis-momentum ($BM_{i,t}$) as independent variable. Models (2) and (3) add time fixed effects and commodity fixed effects, respectively. Model (4) adds both fixed effects. Models (5) and (6) substitute basis ($B_{i,t}$) and momentum ($M_{i,t}$), respectively, for basis-momentum. Model (7) includes three characteristics jointly. We present the estimated coefficients on the characteristics (λ's) as well as the R^2. t-statistics are presented underneath each estimate and are calculated using standard errors clustered in the time dimension. We present results for the full sample period from August 1960 to February 2014 as well as pre- and post-1986. Panel C presents results for two decompositions of basis-momentum over the full sample period. In the left block of results, we regress futures returns on ($M_{i,t}$) and second-nearby momentum ($M^{T_2}_{i,t}$). In the right block of results we regress futures returns on average curvature and change in slope (see Section 2.3).

	Full sample							Pre-1986	Post-1986
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(7)	(7)
Panel A: Nearby returns ($R^{T_1}_{fut,i,t+1}$)									
λ_{BM}	9.69	9.01	9.36	8.50			8.06	10.92	6.59
(t)	(7.40)	(7.33)	(6.94)	(6.84)			(6.02)	(4.88)	(3.98)
λ_B					-5.47		2.34	3.89	2.58
(t)					(-2.14)		(0.85)	(0.75)	(0.80)
λ_M						1.13	0.46	0.52	0.22
(t)						(2.86)	(1.05)	(0.78)	(0.38)
R^2	0.01	0.17	0.01	0.17	0.17	0.17	0.17	0.21	0.15
Time dummies	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Commodity dummies	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Spreading returns ($R^{T_1}_{fut,i,t+1} - R^{T_2}_{fut,i,t+1}$)									
λ_{BM}	1.86	1.63	1.66	1.38			2.03	1.23	2.24
(t)	(6.53)	(5.72)	(5.71)	(4.73)			(7.02)	(3.03)	(5.73)
λ_B					0.49		0.98	0.55	1.41
(t)					(0.57)		(1.13)	(0.39)	(1.27)
λ_M						-0.14	-0.30	-0.18	-0.39
(t)						(-1.46)	(-2.88)	(-1.15)	(-2.93)
R^2	0.01	0.02	0.01	0.02	0.02	0.02	0.03	0.02	0.03
Time dummies	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Commodity dummies	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Decomposing basis-momentum predictability

	$R^{T_1}_{fut,i,t+1}$	$R^{T_1}_{fut,i,t+1} - R^{T_2}_{fut,i,t+1}$		$R^{T_1}_{fut,i,t+1}$	$R^{T_1}_{fut,i,t+1} - R^{T_2}_{fut,i,t+1}$
λ_M	8.23	1.60	λ_{Curv}	4.99	1.17
(t)	(6.64)	(5.94)		(6.34)	(5.53)
$\lambda^{T_2}_M$	-7.83	-1.93	$\lambda_{\Delta Slope}$	9.39	0.60
(t)	(-5.84)	(-6.83)		(4.01)	(0.88)
R^2	0.17	0.03		0.17	0.03
Time dummies	Yes	Yes		Yes	Yes
Commodity dummies	Yes	Yes		Yes	Yes
Time dummies	Yes	Yes		Yes	Yes
Commodity dummies	Yes	Yes		Yes	Yes

Table A.5: Time-series predictability

This table presents results from two tests that analyze whether lagged basis-momentum predicts nearby (left block of results) and spreading (right block of results) returns in the time-series of an individual commodity. In Panel A, we first present for each of 21 commodities (full names are matched to the mnemonics in Table A.1 of the paper) average nearby and spreading returns conditioning on the sign of lagged basis-momentum, and we test the difference ($\mu_{diff} = \mu(R_{fut,i,t+1}|BM_{i,t} > 0) - \mu(R_{fut,i,t+1}|BM_{i,t} \leq 0)$). Next, we present the coefficient (δ_{BM}), t-statistic, and R^2 from a time-series regression of returns on lagged basis-momentum. Panel B counts the the number of commodities (out of 21) for which the difference and the coefficient, respectively, are positive or negative. As a benchmark, we also present the counts when using as signal $X_{i,t}$ either basis ($B_{i,t}$) or momentum ($M_{i,t}$). We test significance at the 10%-level using White heteroskedasticity-robust standard errors. Throughout, we use all the returns available for a particular commodity, which means the total sample period differs across commodities. There is one observation less for the case of basis in Panel B, because gold is always in contango.

Panel A: Futures returns versus lagged signals

	Nearby returns ($R^{T_1}_{fut,i,t+1}$)							Spreading returns ($R^{T_1}_{fut,i,t+1} - R^{T_2}_{fut,i,t+1}$)						
Mnemonic	$\mu(R_{t+1}\|BM_{i,t} > 0)$	$\mu(R_{t+1}\|BM_{i,t} \leq 0)$	μ_{diff}	(t)	δ_{BM}	(t)	R^2*100	$\mu(R_{t+1}\|BM_{i,t} > 0)$	$\mu(R_{t+1}\|BM_{i,t} \leq 0)$	μ_{diff}	(t)	δ_{BM}	(t)	R^2*100
CL	24.20	2.89	21.30	(1.75)	0.99	(1.25)	0.10	2.02	-2.13	4.15	(2.53)	0.28	(2.45)	1.47
HU/RB	12.24	25.13	-12.89	(-0.96)	-0.05	(-0.06)	-0.30	0.40	3.78	-3.38	(-1.40)	-0.08	(-0.46)	-0.21
HO	15.33	4.75	10.58	(1.02)	0.36	(0.35)	-0.20	2.85	-0.35	3.20	(1.86)	0.12	(0.84)	-0.07
KC	33.07	-7.39	40.46	(3.05)	1.21	(1.56)	0.62	5.63	-0.34	5.97	(1.86)	-0.01	(-0.03)	-0.21
RR	-18.69	-4.58	-14.11	(-0.91)	1.17	(1.42)	0.66	-2.51	-3.94	1.43	(0.36)	0.39	(1.19)	1.88
JO	9.78	0.70	9.08	(0.94)	0.67	(0.78)	-0.06	0.79	-0.17	0.96	(0.62)	-0.04	(-0.22)	-0.16
CC	13.43	-0.53	13.96	(1.40)	1.79	(2.00)	1.41	1.91	-0.54	2.45	(1.53)	0.13	(0.84)	0.28
BO	14.22	2.59	11.63	(1.31)	1.77	(2.17)	1.91	1.79	-0.24	2.02	(1.75)	0.24	(1.78)	2.69
SM	17.87	2.87	15.00	(1.89)	1.65	(3.00)	3.17	0.84	-1.42	2.26	(1.51)	0.12	(0.95)	0.40
S-	11.93	3.09	8.84	(1.20)	0.82	(1.46)	0.49	-2.00	-0.87	-1.14	(-0.62)	-0.16	(-0.91)	0.43
C-	8.25	-6.07	14.32	(2.08)	1.26	(1.36)	0.36	0.21	-2.04	2.25	(1.51)	0.17	(1.00)	0.13
O-	8.89	-7.91	16.80	(2.12)	0.93	(1.94)	0.75	1.22	-1.29	2.52	(1.28)	0.36	(2.93)	2.31
W-	14.76	-7.58	22.34	(2.90)	1.83	(2.79)	2.11	1.99	-3.08	5.07	(3.46)	0.43	(3.82)	3.97
CT	14.49	-2.67	17.16	(2.18)	1.65	(3.17)	2.02	-1.32	-1.66	0.33	(0.16)	0.14	(1.08)	0.12
GC	-0.89	5.75	-6.64	(-1.05)	-0.44	(-0.04)	-0.22	0.17	-0.10	0.28	(1.80)	0.10	(0.28)	-0.07
SI	10.76	0.75	10.01	(1.10)	5.21	(0.53)	0.24	-0.03	-0.35	0.32	(1.39)	0.31	(1.66)	2.04
HG	26.96	2.32	24.64	(3.12)	1.37	(1.39)	0.75	2.50	-0.06	2.56	(1.86)	0.10	(0.62)	0.07
LB	12.98	-12.96	25.94	(3.04)	1.31	(3.67)	2.58	3.50	-5.63	9.13	(3.23)	0.60	(6.05)	5.76
FC	3.03	3.98	-0.95	(-0.20)	0.92	(1.60)	0.32	-0.02	-2.05	2.03	(2.13)	0.53	(4.84)	4.02
LC	8.86	-0.29	9.15	(1.92)	0.80	(2.19)	1.17	3.50	-3.64	7.13	(4.53)	0.47	(4.01)	3.83
LH	16.29	-4.87	21.16	(2.82)	1.09	(4.03)	2.10	1.02	-6.62	7.64	(3.25)	0.55	(6.05)	5.46

Table A.5 continued

Panel B: Counts for basis-momentum, basis, and momentum						
	Nearby returns ($R^{(T_1)}_{fut,i,t+1}$)			Spreading returns ($R^{T_1}_{fut,i,t+1} - R^{T_2}_{fut,i,t+1}$)		
Signal $X_{i,t} =$	$BM_{i,t}$	$B_{i,t}$	$M_{i,t}$	$BM_{i,t}$	$B_{i,t}$	$M_{i,t}$
Average returns when lagged signal $X_{i,t} > 0$ versus $X_{i,t} \leq 0$						
# $\mu_{diff,X} > 0$	17	5	20	19	8	6
# $t_{\mu_{diff,X}} > 1.65$	11	1	9	11	2	1
# $\mu_{diff,X} \leq 0$	4	15	1	2	12	15
# $t_{\mu_{diff,X}} \leq -1.65$	0	4	0	0	5	3
Coefficient δ_X in regression of returns on lagged signal $X_{i,t}$						
# $\delta_X > 0$	19	6	16	17	9	5
# $t_{\delta_X} > 1.65$	9	1	5	9	2	2
# $\delta_X \leq 0$	2	15	5	4	12	16
# $t_{\delta_X} \leq -1.65$	0	7	0	0	1	4

Table A.6: Basis-momentum across the futures curve
This table is similar to table 4 of the paper, but uses the larger set of 32 commodities. The table presents unconditional performance measures from sorting commodities on alternative measures of basis-momentum. We consider the performance of High4-minus-Low4 portfolios in second- and third-nearby futures returns ($R^{T_2}_{fut,s}$ and $R^{T_3}_{fut,s}$) as well as spreading returns between the second- and third-nearby and the third- and fourth-nearby contracts ($R^{T_2}_{fut,s} - R^{T_3}_{fut,s}$ and $R^{T_3}_{fut,s} - R^{T_4}_{fut,s}$). In the first block of results, commodities are sorted on our usual measure of basis-momentum, BM_t. The next two blocks of results sort commodities on basis-momentum measured using farther-from-expiring contracts, denoted $BM_t^{2,3}$ and $BM_t^{3,4}$, respectively. For these sorts, we also present performance statistics using only those months where less than or equal to three (out of eight) commodities in the High4 and Low4 portfolios overlap between BM_t and one of the two alternative measures (denoted, e.g., $BM_t^{2,3}|BM_t$). The sample period is from August 1960 to February 2014.

		Average returns for High4-Low4 portfolio			
		$R^{T_2}_{fut,s}$	$R^{T_2}_{fut,s} - R^{T_3}_{fut,s}$	$R^{T_3}_{fut,s}$	$R^{T_3}_{fut,s} - R^{T_4}_{fut,s}$
BM_t	Avg. Ret.	17.92	3.21	16.21	2.28
	(t)	(6.55)	(5.39)	(6.19)	(3.27)
	Sharpe	0.89	0.76	0.87	0.56
$BM_t^{2,3}$	Avg. Ret.	16.79	2.47		
	(t)	(6.39)	(4.07)		
	Sharpe	0.87	0.56		
$BM_t^{2,3}\|BM_t$	Avg. Ret.	12.17	2.79		
(329 Months)	(t)	(3.35)	(3.16)		
	Sharpe	0.64	0.60		
$BM_t^{3,4}$	Avg. Ret.			10.32	0.87
	(t)			(4.07)	(1.67)
	Sharpe			0.56	0.23
$BM_t^{3,4}\|BM_t$	Avg. Ret.			12.66	0.92
(436 Months)	(t)			(3.95)	(1.38)
	Sharpe			0.66	0.23

Table A.7: Time-series predictability of spot and roll returns
This table presents for the sample of 21 commodities (full names are matched to the mnemonics in Table A.1) the predictive coefficients (η_{BM}, η_{BM}^{spot}, and η_{BM}^{roll}) from a regression of nearby, spot, and roll returns on basis-momentum (see Equations (19), (20), (21)). Following the approach of Fama and French (1987), the left hand side first-nearby returns are log holding period returns, which equal the sum of the first-nearby roll return at the beginning of the holding period and the spot return of the first-nearby contract over the holding period, i.e., in between two roll dates. We test significance at the 10%-level using White heteroskedasticity-robust standard errors. Throughout we use all the returns available for a particular commodity, which means the total sample period differs across commodities. Note, given that we measure the basis using the price difference of two futures contract it is exactly equal to the negative of the roll return of the first-nearby strategy. For this reason, we omit the test of significance here.

	Nearby ($r^{T_1}_{fut,i,t+1:t+T_1}$)			Spot ($r^{spot}_{fut,i,t+1:t+T_1}$)			Roll ($r^{roll}_{fut,i,t+1:t+T_1}$)		
	η_{BM}	(t)	R^2*100	η_{BM}^{spot}	(t)	R^2*100	η_{BM}^{roll}	(t)	R^2*100
CL	1.03	(1.37)	0.13	-0.76	(-0.96)	-0.05	1.79	(9.51)	30.78
HU/RB	-0.02	(-0.02)	-0.30	-1.71	(-1.99)	0.81	1.69	(6.92)	12.11
HO	0.23	(0.24)	-0.23	-1.49	(-1.39)	0.49	1.72	(5.46)	13.54
KC	1.85	(0.87)	0.51	-2.00	(-1.09)	0.71	3.85	(8.53)	58.58
RR	3.06	(1.89)	1.98	3.43	(1.62)	2.05	-0.37	(-0.46)	-0.30
JO	0.93	(0.59)	-0.23	-2.88	(-1.88)	0.90	3.81	(3.12)	26.80
CC	3.08	(1.59)	1.71	-0.59	(-0.31)	-0.30	3.66	(10.29)	49.12
BO	2.29	(1.92)	2.14	0.50	(0.41)	-0.12	1.79	(7.17)	31.98
SM	2.39	(2.82)	4.64	2.14	(2.25)	3.49	0.25	(0.82)	0.79
S-	1.55	(1.86)	1.21	1.61	(1.45)	1.19	-0.05	(-0.12)	-0.24
C-	3.01	(1.26)	0.92	0.18	(0.07)	-0.37	2.83	(3.62)	10.37
O-	2.11	(2.77)	1.97	-0.84	(-1.21)	-0.02	2.95	(7.36)	34.92
W-	4.12	(2.93)	4.69	1.56	(1.00)	0.28	2.57	(4.99)	14.69
CT	4.18	(3.40)	4.46	1.16	(0.60)	-0.08	3.01	(2.42)	9.77
GC	-3.07	(-0.13)	-0.40	-7.03	(-0.31)	-0.22	3.96	(3.55)	8.40
SI	19.38	(1.16)	1.89	17.27	(1.01)	1.44	2.11	(3.74)	7.64
HG	2.80	(1.68)	1.39	-0.61	(-0.34)	-0.23	3.40	(9.86)	47.26
LB	2.74	(3.94)	5.03	-0.78	(-1.02)	0.02	3.53	(14.56)	53.11
FC	1.63	(2.08)	0.97	0.30	(0.34)	-0.30	1.33	(4.88)	6.28
LC	1.82	(3.13)	3.69	-0.09	(-0.12)	-0.34	1.90	(6.64)	13.99
LH	1.81	(4.09)	3.54	0.47	(0.85)	-0.15	1.34	(3.26)	3.51

Table A.8: Volatility and basis and momentum portfolios

This table is similar to table 8 of the paper and presents results from two tests that link the basis- and momentum-sorted portfolios to volatility. Aggregate commodity market variance, var_t^{mkt}, is calculated as the sum of squared daily returns on an equal-weighted commodity index, and average commodity market variance, var_t^{avg}, is calculated as the equal weighted average of the sum of squared daily returns of individual commodities. Both variance series are winsorized at the 1%-level and standardized to accommodate interpretation. Panel A presents coefficient estimates, v_{var}, from time series regressions of basis-momentum (nearby and spreading) High4-minus-Low4 portfolio returns (compounded over horizons of $k = 1, 12$ months) on lagged variance. Panel B presents coefficient estimates, nu_{var}, from time series regressions of nearby and spreading returns on contemporaneous monthly innovations in the variance series. To conserve space, we present only the estimated coefficient, v_1, with its t-statistic computed using Newey-West standard errors with k lags. The sample period is August 1960 to February 2014.

Panel A: Does volatility predict High4-Low4 basis and momentum returns?

	Nearby returns ($R^{T_1}_{fut,p,t+1:t+k}$)				Spreading returns ($R^{T_1}_{fut,p,t+1:t+k} - R^{T_2}_{fut,p,t+1:t+k}$)			
	Basis		Momentum		Basis		Momentum	
k	1	12	1	12	1	12	1	12
v_{var}^{mkt}	-7.51	-3.84	-2.22	-4.11	0.27	-0.81	-1.42	-0.08
(t)	(-1.98)	(-0.95)	(-0.49)	(-2.47)	(0.30)	(-1.59)	(-1.27)	(-0.29)
R^2	0.01	0.02	0.00	0.03	0.00	0.02	0.01	0.00
v_{var}^{avg}	-4.47	-2.12	-3.84	-3.24	0.84	-0.23	-1.94	-0.07
(t)	(-1.33)	(-0.55)	(-0.87)	(-1.63)	(0.91)	(-0.34)	(-1.88)	(-0.19)
R^2	0.00	0.00	0.00	0.02	0.00	0.00	0.01	0.00

Panel B: Are High4-Low4 basis and momentum returns exposed to volatility risk?

	Nearby returns ($R^{T_1}_{fut,p,t+1:t+k}$)		Spreading returns ($R^{T_1}_{fut,p,t+1} - R^{T_2}_{fut,p,t+1}$)	
	Basis	Momentum	Basis	Momentum
ν_{var}^{mkt}	5.78	-5.95	-0.20	-0.22
(t)	(2.41)	(-2.02)	(-0.27)	(-0.34)
ν_{var}^{avg}	2.60	-1.44	0.00	0.05
(t)	(2.02)	(-0.99)	(0.00)	(0.19)

Table A.9: Basis-momentum factors versus benchmark commodity factors (32 commodities)

This table is similar to table 9 of the paper, but uses the larger set of 32 commodities to construct the commodity factors. Panel A of this table presents summary statistics for the basis-momentum nearby and spreading factors, which are constructed as the nearby ($R^{nearby}_{BM,t+1}$) and spreading ($R^{spread}_{BM,t+1}$) return of the High4-minus-Low4 portfolio from univariate sorts of 32 commodities. To benchmark these new factors, we also present summary statistics for the factors in two recently developed commodity pricing models. The first model (1) of Szymanowska et al. (2014) contains three factors, which are all constructed from a sort on the basis: (i) the nearby return for the High4-minus-Low4 basis portfolio ($R^{nearby}_{B,t+1}$), (ii) the spreading return of the High4 basis portfolio ($R^{spread}_{B,High4,t+1}$), and (iii) the spreading return of the Low4 basis portfolio ($R^{spread}_{B,Low4,t+1}$). The second model (2) of Bakshi et al. (2015) contains three nearby return factors: (i) a market index ("the average factor", $R^{nearby}_{AVG,t+1}$), (ii) the nearby return for the High4-minus-Low4 basis portfolio (as in the model of de Szymanowska et al. (2014)), and (iii) the nearby return for the High4-minus-Low4 momentum portfolio ($R^{nearby}_{M,t+1}$). Panel B presents spanning tests that ask whether the basis-momentum factors provide an abnormal return over these two benchmark models. We present results for the full sample period from August 1960 to February 2014. The last two columns of Panel B summarize the spanning regressions for two subsamples, split around January 1986. t-statistics are presented underneath each estimate and are calculated using Newey-West standard errors with lag length one.

Panel A: Summary statistics

	Avg. ret.	St.Dev.	Skew.	Kurt.	AR(1)	Correlations $R^{nearby}_{BM,t+1}$	$R^{nearby}_{B,t+1}$,	$R^{nearby}_{AVG,t+1}$	$R^{nearby}_{M,t+1}$	$R^{spread}_{BM,t+1}$	$R^{spread}_{B,High4,t+1}$
$R^{nearby}_{BM,t+1}$	22.09	23.17	0.58	6.86	0.08						
$R^{nearby}_{B,t+1}$ (1),(2)	-7.68	22.36	0.07	6.35	0.10	-0.41					
$R^{nearby}_{AVG,t+1}$ (2)	5.61	13.27	0.13	7.03	0.06	0.00	-0.01				
$R^{nearby}_{M,t+1}$ (2)	18.65	27.24	0.33	5.02	0.03	0.34	-0.35	0.15			
$R^{spread}_{BM,t+1}$	5.04	5.76	1.00	8.89	-0.01	0.52	-0.26	-0.01	0.17		
$R^{spread}_{B,High4,t+1}$ (1)	-1.32	3.24	0.20	5.02	0.08	-0.18	0.36	0.15	-0.14	-0.29	
$R^{spread}_{B,Low4,t+1}$ (1)	-0.77	5.15	0.80	14.14	-0.03	0.15	-0.42	0.07	0.11	0.28	-0.01

Panel B: Basis-momentum factors on benchmark factor models

	Full sample α_{BM}	β^{nearby}_{B}	$\beta^{spread}_{B,High4}$	$\beta^{spread}_{B,Low4}$	β^{nearby}_{AVG}	β^{nearby}_{M}	R^2	Pre-1986 α_{BM}	Post-1986 α_{BM}
Basis-momentum nearby factor									
$R^{nearby}_{BM,t+1}$	18.44	-0.42	-0.23	-0.11			0.17	17.61	18.69
	(6.15)	(-7.37)	(-0.90)	(-0.40)				(4.50)	(3.83)
$R^{nearby}_{BM,t+1}$	16.11	-0.34			-0.06	0.20	0.21	16.64	15.43
	(5.65)	(-5.08)			(-0.78)	(3.62)		(4.13)	(3.78)
Basis-momentum spreading factor									
$R^{spread}_{BM,t+1}$	4.53	-0.01	-0.48	0.30			0.16	2.01	6.58
	(6.11)	(-1.01)	(-6.02)	(3.58)				(2.40)	(5.33)
$R^{spread}_{BM,t+1}$	4.27	-0.06			-0.01	0.02	0.07	2.15	6.20
	(5.70)	(-3.19)			(-0.83)	(2.10)		(2.14)	(5.66)

Table A.10: Cross-sectional asset pricing tests for commodity factor models (32 commodities)
This table is similar to Table 10 in the paper, but uses the larger set of 32 commodities to construct both the factors and portfolios for the asset pricing test. The table presents cross-sectional asset pricing tests for six candidate commodity factor models. The first model of Szymanowska et al. (2014) contains the basis nearby factor ($R^{nearby}_{B,t+1}$) as well as the spreading return of both the High4 and Low4 basis portfolio ($R^{spread}_{B,High4,t+1}$ and $R^{spread}_{B,Low4,t+1}$). The second model of Bakshi et al. (2015) contains three nearby factors: a market index ("the average factor", $R^{nearby}_{AVG,t+1}$), a basis factor ($R^{nearby}_{B,t+1}$), and a momentum factor ($R^{nearby}_{M,t+1}$). The third and fourth model add the basis-momentum nearby factor ($R^{nearby}_{BM,t+1}$) to these two models. The fifth model is a two-factor model including the average commodity market index and the basis-momentum nearby factor. The sixth model adds the basis-momentum spreading factor to this specification ($R^{spread}_{BM,t+1}$). The portfolio-level test in Panel A regresses the average returns of 32 commodity-sorted portfolios (that is, the nearby and spreading return of 9 portfolios sorted on basis-momentum, basis, and momentum (the High4, Mid, and Low4 portfolio from each of these sorts) and 7 sector portfolios (Energy, Grains, Industrial Materials, Meats, Metals, Oilseeds, and Softs)) on their full sample exposures. The commodity-level test in Panel B conducts monthly Fama and MacBeth (1973) cross-sectional regressions of the nearby and spreading returns of 32 commodities on their historical exposure, estimated over a one year rolling window of daily returns. Due to the staggered introduction of commodities in the sample, the size of the cross-section is also time-varying. We present the estimated prices of risk (γ) with corresponding t-statistics in parentheses underneath each estimate (the standard errors are calculated following Shanken (1992) in Panel A and Fama and MacBeth (1973) in Panel B). Also, we present the cross-sectional R^2 and the mean absolute pricing error ($MAPE$, in brackets), which is further decomposed in the $MAPE$ among nearby returns and spreading returns. These measures follow from a regression of average returns on full sample betas in Panel A and average returns on average betas in Panel B. We present results for the full sample period from August 1960 to February 2014, but also summarize the evidence for two subsamples, split around January 1986, focusing on the price of risk for the nearby basis-momentum factor and cross-sectional fit.

Table A.10 continued

	Full sample										Pre- versus post-1986			
	γ_0	γ_{BM}^{nearby}	γ_{B}^{nearby}	γ_{AVG}^{nearby}	γ_{M}^{nearby}	γ_{BM}^{spread}	$\gamma_{B,High4}^{spread}$	$\gamma_{B,Low4}^{spread}$	R^2 $MAPE$	$MAPE_{nearby}$ $MAPE_{spread}$	γ_{BM}^{nearby}	R^2 $MAPE$	γ_{BM}^{nearby}	R^2 $MAPE$
Panel A: Portfolio-level test with full sample betas														
Model 1	1.42		-20.25				2.79	-3.58	0.46	[3.92]		0.56		0.31
	(1.93)		(-5.54)				(1.73)	(-2.25)	[3.09]	[2.25]		[3.18]		[3.27]
Model 2	-0.73		-13.18	5.91	21.22				0.78	[2.41]		0.77		0.76
	(-2.78)		(-4.13)	(3.16)	(5.57)				[1.62]	[0.83]		[1.89]		[1.87]
Model 3	1.33	23.02	-13.37				2.60	-3.30	0.64	[3.40]	20.79	0.70	25.64	0.58
	(1.84)	(6.70)	(-3.92)				(1.65)	(-2.11)	[2.71]	[2.03]	(3.99)	[2.78]	(4.93)	[2.72]
Model 4	-0.84	21.50	-9.03	5.94	19.11				0.92	[1.58]	23.49	0.93	20.10	0.86
	(-3.20)	(6.37)	(-2.90)	(3.18)	(5.02)				[1.14]	[0.70]	(4.84)	[1.09]	(4.05)	[1.68]
Model 5	-0.99	24.05		6.30					0.88	[2.03]	25.95	0.90	22.06	0.81
	(-3.64)	(6.73)		(3.36)					[1.35]	[0.66]	(5.44)	[1.13]	(3.98)	[1.78]
Model 6	-1.05	23.63		6.32		5.71			0.89	[1.88]	25.40	0.91	21.64	0.82
	(-3.72)	(6.61)		(3.37)		(3.53)			[1.31]	[0.74]	(5.34)	[1.25]	(3.90)	[1.73]
Panel B: Commodity-level test with historical betas														
Model 1	1.72		-11.89				1.39	1.94	0.49	[3.69]		0.14		0.64
	(2.19)		(-2.68)				(1.05)	(1.08)	[2.86]	[2.03]		[3.42]		[2.52]
Model 2	-0.03		-17.13	4.87	-4.41				0.77	[2.78]		0.46		0.80
	(-0.08)		(-3.64)	(2.60)	(-0.85)				[1.98]	[1.18]		[2.54]		[1.98]
Model 3	1.34	13.79	-12.47				1.42	2.06	0.53	[3.54]	15.41	0.12	11.63	0.67
	(1.86)	(3.13)	(-2.70)				(1.12)	(1.21)	[2.73]	[1.93]	[2.37]	[3.55]	[1.93]	[2.33]
Model 4	-0.07	14.75	-13.36	4.92	-2.46				0.77	[2.71]	13.08	0.48	14.23	0.81
	(-0.18)	(3.33)	(-2.73)	(2.64)	(-0.45)				[1.96]	[1.21]	[2.12]	[2.53]	[2.26]	[1.91]
Model 5	0.18	12.44		4.47					0.63	[3.68]	11.42	0.32	12.69	0.63
	(0.41)	(2.91)		(2.36)					[2.42]	[1.17]	[1.87]	[2.97]	[2.10]	[2.55]
Model 6	0.24	12.59		4.41		-0.09			0.67	[3.42]	11.51	0.35	12.29	0.68
	(0.56)	(2.94)		(2.34)		(-0.06)			[2.15]	[0.88]	[1.85]	[2.73]	[2.07]	[2.28]

Table A.11: Cross-sectional asset pricing tests: Basis-momentum versus volatility risk

This table is similar to Table 11 of the paper, but uses the larger sample of 32 commodities to construct the portfolios that are used as test assets in the cross-sectional regressions that test the relation between the pricing of basis-momentum and volatility risk. We consider five models. The first model contains the average nearby factor ($R^{nearby}_{AVG,t+1}$) as well as the basis-momentum nearby factor ($R^{nearby}_{BM,t+1}$). The second and third model replace the basis-momentum factor with non-traded innovations in commodity and stock market variance, i.e., Δvar^{com}_{t+1} and Δvar^{eq}_{t+1}, respectively. In models four and five, we include both basis-momentum and the innovations. We regress the average returns of 32 commodity-sorted portfolios (that is, the nearby and spreading return of 9 portfolios sorted on basis-momentum, basis, and momentum (the High4, Mid, and Low4 portfolio from these sorts) and 7 sector portfolios (Energy, Grains, Industrial Materials, Meats, Metals, Oilseeds, and Softs)) on their full sample exposures. We present the estimated prices of risk (γ) with corresponding Shanken (1992) t-statistics in parentheses underneath each estimate. Also, we present the cross-sectional R^2 and the mean absolute pricing error ($MAPE$, in brackets), which is further decomposed in the $MAPE$ among nearby returns and spreading returns. We present results for the full sample period from August 1960 to February 2014.

	γ_0	γ^{nearby}_{AVG}	γ^{nearby}_{BM}	γ^{mkt}_{var}	γ^{avg}_{var}	R^2 $MAPE$	$MAPE_{nearby}$ $MAPE_{spread}$
Model 1	-0.99	6.30	24.05			0.88	[2.03]
	(-3.64)	(3.36)	(6.73)			[1.35]	[0.66]
Model 2	-1.48	7.36		-0.09		0.66	[3.06]
	(-3.93)	(3.82)		(-3.56)		[2.02]	[0.97]
Model 3	-1.08	7.32			-0.33	0.56	[3.75]
	(-2.50)	(3.71)			(-2.50)	[2.32]	[0.89]
Model 4	-1.14	6.59	22.67	-0.03		0.89	[1.84]
	(-3.93)	(3.51)	(6.53)	(-1.34)		[1.28]	[0.72]
Model 5	-1.02	6.56	23.34		-0.09	0.89	[1.89]
	(-3.56)	(3.48)	(6.56)		(-1.03)	[1.28]	[0.66]