Basis-momentum in the futures curve and volatility risk *

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Abstract

We introduce a commodity-return predictor related to slope and curvature of the futures curve: basis-momentum. Basis-momentum strongly outperforms benchmark characteristics in predicting spot and term premiums in the time-series and cross-section. Basis-momentum is maturity-specific, driven by roll returns, present in currencies and stock indexes, and increasing in volatility. Asset pricing tests show that a parsimonious two-factor model provides an excellent fit for the cross-section of commodities, with a large premium for basis-momentum that represents compensation for volatility risk. We argue that basis-momentum is driven by maturity-specific price pressures that materialize when increasing volatility reduces the ability of speculators to clear the market.

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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In this paper, 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 of commodity returns to date in three important dimensions: cross section, time series, and maturity. A long history of literature studies stock and bond risk premiums along these exact dimensions. Basis-momentum is important for investors as well, because the recent financialization of commodity markets has inspired large and increasingly active institutional investment.[1]

We argue that basis-momentum is driven by maturity-specific price pressures that materialize when increasing volatility reduces the ability of speculators to clear the market. This economic explanation follows, among others, Brunnermeier and Pedersen (2009), Brunnermeier et al. (2009), and Nagel (2012), who argue that the tight link between liquidity and volatility has important asset pricing implications. We perform a wide variety of analyses to support this argument, among which the most important are linking basis-momentum to (market-wide) volatility and liquidity, and performing out-of-sample tests for currencies and stock indexes. We show 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 largely represents compensation for volatility and liquidity risk. We conclude that a parsimonious two-factor model, including basis-momentum and 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-nearby futures strategies. A simple decomposition shows that basis-momentum is determined by 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 and spreading returns (from combining a long position in a nearby contract with a short position in a farther-from-

[1]For recent work on the financialization, see, e.g., Tang and Xiong (2012), Cheng et al. (2014), Basak and Pavlova (2015), and Sockin and Xiong (2015).

expiring contract) with a positive sign. Likewise, persistence in the steepening (flatterning) of the slope should predict nearby returns in absolute terms and relative to farther-from-expiring returns.[2] Since cross-sectional and time-series variation in basis-momentum are large for commodities (relative to currencies and stock indexes), this market provides us with an ideal laboratory for analyzing basis-momentum predictability.

Our first contribution is in showing that basis-momentum strongly outperforms benchmark characteristics, such as basis and momentum, in predicting commodity futures returns since the inception of trading in 1959.[3] This conclusion holds for both (first-) nearby returns and (first-minus-second-nearby) spreading returns as well as in both the time series and cross section. As shown in Szymanowska et al. (2014), nearby and spreading returns, respectively, capture commodity spot and term premiums, analogous to bonds. In the cross section, sorting 21 commodities on basis-momentum leads to a large average annualized difference between the high and low portfolio of 18.38% ($t = 6.73$) in nearby returns and 4.08% ($t = 6.43$) in spreading returns.[4] In pooled regressions that control for systematic differences across commodities, a standard deviation increase in basis-momentum predicts a large and significant increase in monthly nearby (spreading) return of 0.85% (0.20%).

Decomposing basis-momentum, we draw two additional conclusions. First, although both curvature and slope contribute to the excellent performance of basis-momentum, it is curvature that contributes more. This finding is important because benchmark characteristics, such as basis and momentum, are not directly related to curvature. 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.

[2]Cochrane (2011) similarly uses changes in book-to-market and dividend yield instead of their more commonly used levels to predict stock returns (see Tables AII and AIII of his paper).

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

[4]These returns survive estimates of transaction costs based on the evidence in Marshall et al. (2012) and are also present in a larger cross-section of 32 liquidly traded commodities.

Our second contribution is in studying the economic drivers of basis-momentum predictability. To start, we present a range of analyses that suggest basis-momentum is unlikely to be driven by classical commodity futures pricing theories. The theory of storage cannot explain the basis-momentum effect, because (i) we find similarly large basis-momentum effects among more and less storable commodities; (ii) the basis-momentum effect is driven by roll returns, whereas spot prices are impacted directly by storage and inventory decisions for the physical commodity (see Kaldor (1939), Working (1949), and Deaton et al. (1992)); (iii) basis-momentum predicts returns controlling for basis and momentum, which factors Gorton et al. (2013) argue to be compensation for inventory risk; and, (iv) basis-momentum predicts returns in cross-sections of 48 currencies and twelve stock indexes, which financial assets can be stored costlessly. The fact that basis-momentum exists across asset classes indicates that basis-momentum is of general asset pricing interest. A standard hedger's price pressure (Cootner's (1960, 1967)) is not likely to explain our results either.[5] The principal ideas of Cootner say nothing about spreading returns, whereas we show that basis-momentum predictability is maturity-specific using first- to fourth-nearby contract returns. Moreover, the basis-momentum effect is not driven out when controlling for hedging pressure measured using the Commitment of Trader reports of the Commodity Futures Trading Commission (CFTC).

Given this wealth of evidence, the most plausible explanation for basis-momentum is maturity-specific price pressure, where the relative demand of hedgers versus speculators varies across contracts of a single commodity. We are the first in the literature to argue that an extension of the classic theory is necessary to fully understand commodity futures return variation. Unfortunately, we cannot test for maturity-specific price pressure directly using public CFTC data, because this data is aggregated across the curve. However, sug-

[5]Hedger's price pressure is a reinterpretation of the theory of normal backwardation of Keynes (1930), and links futures risk premiums to the net demand of producers and consumers relative to speculators. When short producers (long consumers) dominate the group of hedgers, the futures price is set below (above) the expected future spot price to convince risk-averse speculators to clear the market.

gestively consistent with this hypothesis, our double sorts show that the interaction between basis-momentum and aggregate price pressure variables contains independent information about nearby and spreading returns. Moreover, there is clearly important information in the decisions of investors to establish a position at different locations on the futures curve. On one hand, we find that basis-momentum is unrelated to seasonalities in commodity returns that are mostly driven by variation in hedging demands of producers and consumers. On the other hand, it is well-known that commodity investors, and speculators in particular, trade continuously on information extracted from the shape of the futures curve. Kang et al. (2016) argue that speculator's trades often take liquidity and thus influence prices in a manner opposite to what the standard theory of hedging pressure suggests. Also, contracts farther down the futures curve are typically less liquid, but may also be attractive to reduce the number of roll dates and transaction costs. And, finally, time-variation in volatility and its term structure are key determinants for the investment decisions of both hedgers and speculators.[6]

Motivated by these observations, we investigate the relation between liquidity, volatility, and basis-momentum. In closely related work, Brunnermeier et al. (2009) and Nagel (2012) investigate the relation between liquidity, volatility, and returns of, respectively, the currency carry trade and short-term reversal strategies in the stock market. Among 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. If increasing volatility is associated to widening imbalances of supply and demand within and across commodity futures curves, this model has two implications for the basis-momentum strategy that we confirm in the data.[7] First, nearby and spreading basis-momentum returns are increasing in volatility. We

[6]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.

[7]Consistent with this association, we find a large positive correlation between volatility and the basis-

consider both aggregate and average commodity market volatility to ensure that we capture risk that is relevant for diversified commodity investors as well as traditional hedgers and specialized speculators. Second, basis-momentum exposes investors to volatility-shocks, which implies that basis-momentum is a risky factor. Our double sorts show that the basis-momentum effect is larger for illiquid, high volatility commodities, that is, commodities where the expected returns to liquidity provision are likely largest. Furthermore, the fact that the basis-momentum effect is larger for commodities than for currencies and stock indexes is consistent with the idea that the average commodity is relatively illiquid.

Our third contribution is 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). We construct a basis-momentum factor and run asset pricing tests for the broadest cross-section of commodity returns studied to date, including both nearby and spreading returns of either a range of portfolios (sorted on characteristics and sectors) or individual commodities. 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 from these benchmark factors. The risk premium we estimate is close to the sample average return of the basis-momentum factor, which is an important reality check, and translates to 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

momentum characteristic in our sort.

the interpretation that basis-momentum largely represents compensation for priced volatility risk.[8] Evidence that volatility risk is priced in other asset classes is abundant (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 fact that basis-momentum is strongly linked to volatility does not necessarily imply that volatility itself is the only state variable driving expected return variation. More likely, volatility also proxies for underlying state variables that are relevant for the ability of speculators and financial intermediaries to clear the market. Uncovering these underlying state variables is difficult, because liquidity is multi-dimensional and unobservable (Brunnermeier et al. (2009) and Nagel (2012)). However, using simple proxies for market and funding liquidity, we provide additional evidence consistent with a model in which illiquidity is associated to higher volatility, and this association is what is driving imbalances in supply and demand of futures contracts that make basis-momentum returns higher going forward. Our results imply that volatility and liquidity risk are priced much more broadly in commodity markets than was known in the literature.[9] We conclude that basis-momentum is a key input for (commodity) futures pricing models.

The paper is organized as follows. In Section 1, we describe the data and variables we use. In Section 2, we ask whether basis-momentum predicts commodity futures returns and in which dimensions. In Section 3, we analyze how basis-momentum fits into commodity futures pricing theory, run out-of-sample tests for currencies and stock indexes, and link basis-momentum returns to maturity-specific price pressure and volatility. In Section 4, we run cross-sectional asset pricing tests for basis-momentum and volatility risk. In Section 5, we summarize and conclude.

[8]This conclusion generally applies to volatility risk, as exposure to stock market volatility risk is priced similarly among our test assets.

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

1 Data and variable definition

1.1 Commodity futures data and return definitions

We collect data on exchange-traded, liquid commodity futures contracts from the Commodity Research Bureau (CRB), supplemented with data from the Futures Industry Institute. A substantial part of this dataset is identical to Szymanowska et al. (2014), who analyze returns on 21 commodity futures from 1986 to 2010. We extend this dataset to start in July 1959, at the inception of futures trading, and end in February 2014. Also, we append data on eleven liquidly-traded commodities, among which some represent large markets, such as natural gas. 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 first- and second-nearby contracts, because these are the most liquid. We use third- and fourth-nearby contracts in a robustness check. For each contract we calculate excess returns on a fully collateralized position using:

$$R_{fut,t+1}^{T_n} = \frac{F_{t+1}^{T_n}}{F_t^{T_n}} - 1, \tag{1}$$

where $F_{t+1}^{T_n}$ 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, if the nth-nearby contract is expiring in month $t+2$, the nth-nearby strategy rolls into the $n+1$th-nearby contract in month t. This approach avoids holding contracts close to expiration, when erratic price and volume behavior is commonly observed.

In the Appendix to this paper, we decompose expected futures returns in spot and term premiums following Szymanowska et al. (2014). Analogous to the bond market, spot premiums are captured by a long-only position in the first-nearby contract, such that we refer to $R_{fut,t+1}^{T_1}$ as the nearby return. Term premiums are captured by a long-short position in the first-nearby contract and a farther-from-expiring contract, and 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 IA.1 of the Internet Appendix presents summary statistics.

1.2 Variable definition

A long history of literature shows that basis (B_t) and momentum (M_t),

$$B_t = \frac{F_t^{T_2}}{F_t^{T_1}} - 1 \text{ and} \tag{2}$$

$$M_t = \prod_{s=t-11}^{t} (1 + R^{T_1}_{fut,s}) - 1, \tag{3}$$

predict nearby futures returns.[10] Szymanowska et al. (2014) find that basis also predicts spreading returns. In fact, many recently introduced commodity index products take positions conditional on these two characteristics (Miffre (2013)). As such, basis and momentum are the most important benchmarks to test whether any new characteristic has marginal predictive content.

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

$$BM_t = \prod_{s=t-11}^{t} (1 + R^{T_1}_{fut,s}) - \prod_{s=t-11}^{t} (1 + R^{T_2}_{fut,s}). \tag{4}$$

The motivation for this signal is that it contains information about slope and curvature, which are both determined by the decisions of investors (producers, consumers, speculators, and, more recently, index investors) to take positions at different locations on the futures

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

curve. To see why, we use the definition of first- and second-nearby log futures returns in Equations (A.4) and (A.6), and write basis-momentum as

$$\begin{aligned}
\sum_{s=t-11}^{t} r^1_{fut,s} - \sum_{s=t-11}^{t} r^2_{fut,s} &= \sum_{s=t-11}^{t} (s_s - f^1_{s-1}) - \sum_{s=t-11}^{t} (f^1_s - f^2_{s-1}) \\
&= \sum_{s=t-11}^{t} (f^2_{s-1} - f^1_{s-1}) - \sum_{s=t-11}^{t} (f^1_s - s_s) \\
&= \sum_{s=t-11}^{t} b^2_{s-1} - \sum_{s=t-11}^{t} b^1_s, \qquad (5)
\end{aligned}$$

where $b^1_t = f^1_t - s_t$ and $b^2_t = f^2_t - f^1_t$ represent the slope, or basis, measured at two different points on the futures curve. Equation (5) thus decomposes basis-momentum into a measure of 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 $(b^2_{t-12} - b^1_t)$.

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, 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 first-nearby returns in absolute terms and relative to second-nearby returns. As neither basis nor momentum is directly related to curvature, it is economically interesting to see how basis-momentum performs in asset pricing tests relative to these benchmark predictors.[11]

2 Does basis-momentum predict returns?

In this section, we ask whether basis-momentum predicts returns in various dimensions.

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

2.1 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, and Low4) from August 1960 to February 2014. High4 contains the four commodities with the highest ranked 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 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 is monotonic and translates to a Sharpe ratio of about 0.9.

Table 1 further shows that the basis-momentum effect is robust pre- and post-1986, although the effect in spreading returns is larger in the second subsample. In contrast, the basis effect is only large and significant in nearby returns pre-1986. Figure 1 shows that the outperformance of basis-momentum cumulates to a huge difference in the value of a dollar invested over time, without exposing investors to extreme drawdown risk. Table IA.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 the curvature (see footnote 11).[12]

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 shows that the basis-momentum effect (in both nearby and spreading returns) weakens as time passes after sorting in month t, but remains significant until about a year. In contrast, the momentum nearby-effect dies out quickly and the basis nearby-effect strengthens the first few months after sorting. Figure 4 shows that the basis-momentum effect is driven by returns over the last year before portfolio formation, as basis-momentum measured using returns that realized more than one year ago does not predict nearby nor spreading returns.

Given that basis and momentum strategies, which are not too different in stability and composition, are already applied in practice, it is likely 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

[12]Szymanowska et al. (2014) find that the basis predicts spreading returns, but these authors sample data at a lower bi-monthly frequency. The monthly frequency is most common in the literature (see, e.g., Yang (2013), Koijen et al. (2015), and Bakshi et al. (2015)).

one trade using calendar spreads. 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, and halve transaction costs.

2.2 Multivariate tests

Even though the basis-momentum effects 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 characteristics, we now run pooled predictive regressions:

$$R^{T_1}_{fut,i,t+1} = \lambda'_C C_{i,t} + a_{t+1} + \mu_i + e_{i,t+1} \text{ and} \tag{6}$$

$$R^{T_1}_{fut,i,t+1} - R^{T_2}_{fut,i,t+1} = \lambda'_C C_{i,t} + a_{t+1} + \mu_i + e_{i,t+1}. \tag{7}$$

These regressions are additionally interesting, because they split the return predictability from basis-momentum in its passive and dynamic components (Koijen et al. (2015)). 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 $C_{i,t} = \{BM_{i,t}, B_{i,t}, M_{i,t}\}$). Without fixed effects, $\lambda_{BM,t}$ represents the total return predictability from basis-momentum. Including time fixed effects removes the passive component coming from time-variation in average commodity returns, 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. Including both fixed effects, $\lambda_{BM,t}$ captures solely the dynamic component of basis-momentum return predictability.

Panel A of Table 2 presents the results for nearby returns.[13] 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. Consistent with the evidence from our sorts, adding time fixed effects (column two) has little impact on the coefficient estimate. 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).[14] 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.

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.

[13]The standard errors are clustered in the time dimension, because commodity returns are not strongly autocorrelated. Indeed, we find that significance-levels are similar using two-way clustered standard errors.

[14]In unreported results, we find that the basis-momentum effect is also robust to including commodity$\times$calender-month fixed effects, which may capture seasonalities in commodity returns due to variation in hedging demands of producers and consumers.

The last two columns of Panels A and B show largely similar results for the two subsamples split around January 1986, whereas Table IA.3 of the Internet Appendix shows similar evidence for the larger cross section of 32 commodities. Table IA.4 of the Internet Appendix presents commodity-level time series regressions and shows that the coefficients in the pooled regression are driven by predictability for a large number of commodities from various sectors.[15]

In Panel C of Table 2, 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 our measure of average curvature and the change in slope (see Section 1.2), defined as:

$$Curv_t = \sum_{s=t-11}^{t-1} B_s^{T_2} - \sum_{s=t-11}^{t-1} B_s \tag{9}$$

$$\Delta Slope_t = B_{t-12}^{T_2} - B_t; \tag{10}$$

where B_t is the slope between the first- and second-nearby futures prices (as defined in Equation (3)) 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

[15] To be precise, we run regressions of the form:

$$\{R_{fut,i,t+1}^{T_1}, R_{fut,i,t+1}^{T_1} - R_{fut,i,t+1}^{T_2}\} = \delta_{0,i} + \delta_{BM,i} BM_{i,t} + e_{i,t+1} \text{ and} \tag{8}$$

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

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 curvature and change in slope contribute to the excellent performance of basis-momentum as a predictor of commodity returns. The relative contribution of curvature is larger economically and statistically, however, with an increase in monthly nearby (spreading) return of about 0.60% (0.16%) for a standard deviation increase in $Curv_t$ relative to 0.34% (0.05%) for $\Delta Slope_t$.

To ensure the basis-momentum effect is also robust to a range of other characteristics, we 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, momentum, storability (splitting the sample into 15 "more" storable commodities and 17 "less" storable commodities), twelve-month volatility, Amihud (2002) illiquidity, and, finally, hedging and spreading pressure.[16]

Table 3 presents the results for nearby returns in Panel A. Looking at the control variables first, we see that only basis, average basis, and momentum provide a large and significant High-Low spread of around 8%. Controlling for high or low basis-momentum, however, lowers the High-Low spreads for these control variables considerably. In contrast, the basis-momentum effect is economically large and significant in all control groups, although some variation is visible. The basis-momentum effect is larger for commodities with low ver-

[16]Using the evidence Gorton et al. (2013) (in particular, their Table 3), the "more storable" portfolio contains 15 commodities: Soybeans, Soybean meal, Cocoa, Cotton, Feeder Cattle, Oats, Coffee, Corn, Palladium, Lumber, Rubber, Copper, Platinum, Gold, and Silver. As mentioned by the authors, (industrial) metals are relatively easy and cheap to store, and equilibrium inventories are expected to be large on average relative to demand. By comparison, energies are more bulky and expensive to store, and therefore have lower inventories relative to demand. Grains, meats, oilseeds, and softs are more spread out across the "more" and "less" storable portfolios. Amihud illiquidity is calculated for each commodity futures contract as an annual average of daily returns over dollar volume ($R^{T_n}_{fut,i,d}/Vol^{T_n}_{i,d}$). Our illiquidity measure is the average of the Amihud measure for the first- and second-nearby contract ($n = 1, 2$), to ensure we are not focusing on the most liquid first-nearby contract alone. 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.

sus high hedging pressure (19.01% versus 8.62%), high versus low volatility (21.71% versus 13.27%), and high versus low illiquidity (22.15% versus 13.05%). These findings imply that the interaction between basis-momentum and hedging pressure, volatility, and liquidity contains additional information relevant to nearby commodity returns, whereas these control variables are largely uninformative in isolation.[17]

Panel B shows that spreading pressure is the only control variable with a significant High-Low effect in spreading returns at -1.84% ($t = -3.86$). The fact that the total number of spreading positions of non-commercials predicts spreading returns has not been documented in the literature before, but is consistent with the intuition that long-short spreading positions of speculators may cause differential price pressure in a single futures curve. The basis-momentum effect in spreading returns is large and significant in all control groups, although some variation is visible. Most important for our paper, we see that the basis-momentum effect is considerably larger for commodities with high versus low spreading pressure (3.99% versus 2.04%) and high versus low illiquidity (3.58% versus 2.16%). We conclude that basis-momentum predictability is robust to a range of control variables, although it is shown to interact with price pressure variables based on the CFTC's aggregated position data as well as volatility and illiquidity.

In all, the results of this section show that basis-momentum is a powerful and multi-dimensional predictor of commodity futures returns. Basis-momentum predictability revolves around the dynamic components of spot and term premiums and is robust to controlling for benchmark predictors. In fact, the performance of benchmark predictors is considerably less impressive once basis-momentum is controlled for. Basis-momentum is a key input to active commodity trading strategies.

[17]Recent evidence on CFTC-based hedging pressure is consistent with this conclusion (Szymanowska et al. (2014) and Gorton et al. (2013)). Alternative measures of hedging pressure in oil and gas futures markets that deal with the shortcomings in the CFTC hedger classification have had more success (see, e.g., Dewally et al. (2013) and Acharya et al. (2013)).

2.3 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 (4), is able to predict returns of 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

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

$$BM^{3,4}_t = \prod_{s=t-11}^{t} (1 + R^{T_3}_{fut,s}) - \prod_{s=t-11}^{t} (1 + R^{T_4}_{fut,s}). \tag{12}$$

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 our original basis-momentum measure. We see that farther-from-expiring futures returns are predictable with this measure as well, but the effect weakens as the contract is farther from expiration. 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 second-nearby and second-minus-third-nearby returns, 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 original basis-momentum measure. 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 IA.5 presents similar evidence for the larger sample of 32 commodities.

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

3 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 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.

3.1 Maturity-specific 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. In addition, the basis-momentum effect exists among commodities with both high and low hedging pressure (see Table 3). However, if hedger's price pressure varies persistently across contracts of a single commodity, this could drive variation in both spot and term premiums. Suggestively consistent with this hypothesis, we saw already in Table 3 that the interaction between basis-momentum and hedging pressure contains information about nearby returns, whereas the interaction between basis-momentum and spreading pressure contains information about spreading returns. Unfortunately, we cannot test for maturity-specific price pressure directly using public CFTC data, because these data are aggregated at the commodity-level.

On the other hand, we can definitively test against alternative explanations for the basis-momentum effect based on the theory of storage of Kaldor (1939), Working (1949), and Deaton et al. (1992). To this end, we first 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 currencies and stock indexes, for which financial assets 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. Our findings that the basis-momentum effect is robust to controlling for these benchmark predictors and to splitting the sample in more and less storable commodities (see Tables 2 and 3), represent the first pieces of evidence against storage- and inventory-based explanations.

3.1.1 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:

$$R^{spot}_{fut,t+1} = \frac{1 + R^{T_1}_{fut,t+1}}{1 + R^{roll}_{fut,t+1}} - 1, \text{ where} \tag{13}$$

$$R^{roll}_{fut,t+1} = \begin{cases} \frac{F_t^{T_1}}{F_t^{T_2}} - 1, & \text{if } T_1 = t+2 \\ 0, & \text{otherwise.} \end{cases} \tag{14}$$

The first equation uses that, by construction, the futures return combines the spot and roll return.[18] 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 expires after $t+2$. Roll returns are positive in backwardation and negative in contango.

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%. This finding is perhaps unsurprising given that basis-momentum strongly predicts spreading returns that do not contain a spot return component (see Appendix). Consistent with the fact that the nearby roll return is equal to the negative of the basis (see Equation (A.8)), 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 basis strategy are 37.92%, consistent with the idea that futures prices contain information

[18]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.

about expected future spot prices.[19] 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 (see Fama and French (1987)):

$$r^{T_1}_{fut,i,t+1:t+T_1} = \eta_{0,i} + \eta_{BM,i} BM_{i,t} + v_{i,t+1:t+T_1}, \tag{15}$$

$$r^{roll}_{fut,i,t+1:t+T_1} = \eta^{roll}_{0,i} + \eta^{roll}_{BM,i} BM_{i,t} + v^{roll}_{i,t+1:t+T_1}, \text{ and} \tag{16}$$

$$r^{spot}_{fut,i,t+1:t+T_1} = \eta^{spot}_{0,i} + \eta^{spot}_{BM,i} BM_{i,t} + v^{spot}_{i,t+1:t+T_1}. \tag{17}$$

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.

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 IA.6 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, basis-momentum does not predict spot returns in more than a few cases. Consistent with Table IA.4 of the Internet Appendix, the number of commodities for which basis-momentum

[19] 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.

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 represents our second piece of evidence against storage- and inventory-based explanations for the basis-momentum effect.

3.1.2 Basis-momentum in currencies and stock indexes

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 Section 1 of the Internet Appendix. We define monthly nearby and spreading currency returns as

$$R^1_{cur,t+1} = S_{t+1}/F^1_t, \text{ and} \tag{18}$$

$$R^{spread}_{cur,t+1} = R^1_{cur,t+1} - F^1_{t+1}/F^2_t. \tag{19}$$

Our sample of stock indexes contains 12 markets for which we collect first- and second-nearby futures prices. Returns and sorting variables are constructed analogous to commodities. Due to the staggered introduction of stock indexes in our databases, the sample period with cleanly available nearby ($R^{T_1}_{stock,t+1}$) and spreading ($R^{T_1}_{stock,t+1} - R^{T_2}_{stock,t+1}$) return data runs from August 2001 to December 2014. As in the case of commodities, we sort the currencies and stock indexes into three portfolios using basis-momentum, basis, and momentum.

Table 7 presents the results for currencies in Panel A. We see that currency returns are monotonically increasing in basis-momentum. The nearby and spreading return of the High4-minus-Low4 portfolio are large and significant at 8.06% (t = 3.47) and 0.78% (t = 2.32), respectively. The nearby return translates to a Sharpe ratio of 0.81, which is only slightly below a value of 0.92 for commodities (see Table 1).[20] In Sharpe ratio, the spreading return is considerably smaller than for commodities, at 0.54 relative to 0.88. In Panel B we see that stock index returns are also monotonically increasing in basis-momentum. Both nearby and spreading return for the High4-minus-Low4 portfolio are marginally significant at 4.45% ($t = 2.01$) and 1.01% ($t = 1.82$), respectively. These returns translate to Sharpe ratios around 0.55, which is large economically, but considerably smaller than for commodities.

The existence of a basis-momentum effect in these financial markets represents the third piece of evidence against storage- and inventory-based explanations, but is consistent with our story of maturity-specific price pressure. For instance, domestic (foreign) firms and investors with business in foreign (domestic) currency want to sell (buy) foreign currency forward to hedge, whereas specialized speculators and financial intermediaries are there to clear the market. Thus, if there is variation in the balance between demand and supply of these groups of traders, this will lead to time-varying price pressures at different contract maturities and currency basis-momentum, in much the same way as for commodities. The fact that the basis-momentum effect is largest for commodities and smallest for stock indexes is consistent with our story, as well. Price pressures are likely larger for illiquid assets, and, in our sample, the average commodity is illiquid relative to the average currency and especially relative to the average of twelve developed market stock indexes. In the following, we analyze further implications from the relation between basis-momentum and price pressure, or liquidity more generally.

3.2 Basis-momentum and volatility

To determine how basis-momentum has been able to persist since the introduction of commodity futures trading, we ask how the strategy is related to volatility. This relation

[20] 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 Koijen et al. (2015)). Because our focus is on commodity markets, we leave a thorough investigation of basis-momentum in these financial markets to future work.

can be motivated from the intimate link between liquidity and volatility. Along the lines of, e.g., Brunnermeier and Pedersen (2009): if increasing volatility is associated to widening imbalances of supply and demand within and across commodity futures curves, two implications must hold that we test in the following. First, higher volatility leads to more maturity-specific price pressure and thus higher returns on basis-momentum strategies. Second, basis-momentum strategies are negatively exposed to volatility risk, such that volatility risk is a determinant of risk premiums in commodity markets. Consistent with this hypothesis, we saw already that the basis-momentum effect is larger for illiquid commodities with high volatility, which may proxy for higher expected returns to liquidity provision in the model of Brunnermeier and Pedersen (2009) (see, also, Nagel (2012)).

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, which is similar to the approach of Guo (2006) and Goyal and Welch (2008).[21] 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. The contemporaneous correlation between these volatility measures and the difference in average basis-momentum for the High4-minus-Low4 portfolio is large at about 0.45. This finding is consistent with the hypothesized link between volatility and maturity-specific price pressure as a driver of basis-momentum returns.

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

$$R_{fut,p,t+1:t+k} = v_0 + v_{var} var_t + e_{t+1:t+k}, \tag{20}$$

[21] In a robustness check, we also use their measure of stock market variance, i.e., the sum of squared daily returns on the S&P500.

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, υ_1, with its t-statistic computed using Newey-West standard errors with k lags, and the regression R^2.[22] 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 7.56% for $k = 1$ and 5.78% for $k = 12$ for a standard deviation increase in variance. For spreading returns, the evidence is similarly strong, with an increase in spreading return of 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. Table IA.7 of the Internet Appendix shows larger effects (both economically and statistically) when the predictive regression of Equation (20) is estimated more efficiently by weighted least squares. In Panel B, we present results from an out-of-sample exercise that conditions basis-momentum returns on lagged volatility (relative to its historical median), separating the sample in high volatility months and normal months. We find that High4-minus-Low4 returns are about twice as large after high volatility months, with a significant difference relative to after normal months of 12.99% (nearby returns) and 2.73% (spreading returns). We conclude that commodity market 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:

$$R_{fut,p,t+1} = \nu_0 + \nu_{var} \Delta var_{t+1} + o_{t+1}, \tag{21}$$

where the innovation, Δvar_{t+1}, is measured as a first-difference. Panel C of Table 8 presents the estimated coefficients, ν_{var}, over the full sample as well as during the worst basis-

[22] In this regression, both variance series are winsorized at the 1%-level (to reduce the impact of outliers) and standardized (to accommodate interpretation).

momentum return episodes (defined as months with below median drawdown for the High4-minus-Low4 portfolio). We see that exposures in nearby returns to innovations in aggregate commodity market variance decrease monotonically with basis-momentum over the full sample. 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 change in Δvar_{t+1}^{mkt}. Exposures to innovations in average commodity market volatility (Δvar_{t+1}^{avg}) are similar in magnitude and significance. Exposures to volatility risk are also negative in spreading returns, but small and insignificant over the full sample. However, in drawdown periods, which are economically more interesting perhaps (see also Koijen et al. (2015)), both nearby and spreading returns contain economically large and (marginally) significant exposures to volatility risk. Thus, we can also conclude that basis-momentum exposes investors to volatility risk.

In Table IA.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 is largely consistent with the hypothesis that basis-momentum returns are driven by the intimate relation between volatility and liquidity in the form of maturity-specific price pressure. When volatility is high, speculators and financial intermediaries, more generally, are unable to provide liquidity and require a higher risk premium to clear the market especially for those futures contracts with largest (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 captures a negative price of risk in commodity markets. In Section 4.3 we estimate the price of volatility risk directly in cross-sectional asset pricing tests and dig deeper into the relation between volatility and liquidity.

4 Is basis-momentum a priced commodity risk factor?

In this section, we analyze whether basis-momentum is a priced risk factor in commodity markets. 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.

4.1 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 attractive investment strategies: average returns are high relative to the benchmark factors, whereas standard deviation, skewness, and kurtosis are similar in magnitude. Moreover, the correlations between the factors are all below 0.5 in absolute value, indicating that the factors are sufficiently different to contain 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 and Table IA.9 of the Internet Appendix, respectively, show that these conclusions are robust pre- and post-1986 and for the larger set of 32 commodities. We conclude that basis-momentum strategies provide a large abnormal return.

4.2 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

$$\begin{aligned}R_{t+1} =& \gamma_{0,t} + \gamma_{1,t}\beta^{nearby}_{BM,t} + \gamma_{2,t}\beta^{nearby}_{B,t} + \gamma_{3,t}\beta^{nearby}_{AVG,t} + \gamma_{4,t}\beta^{nearby}_{M,t} + \\ & \gamma_{5,t}\beta^{spread}_{BM,t} + \gamma_{6,t}\beta^{spread}_{B,High4,t} + \gamma_{7,t}\beta^{spread}_{B,Low4,t} + u_{t+1}.\end{aligned} \tag{22}$$

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 may do a good job capturing the level of commodity returns, whereas the basis-momentum factor may 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 (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.[23] 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, we analyze next the cross section of nearby and spreading returns of individual commodities. This approach follows recent literature that performs cross-sectional tests for individual stocks rather than portfolios (see, e.g., Lewellen et al. (2010) and Ang et al. (2011)) and is particularly attractive for commodities, as this cross section is small to begin with 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.[24] We switch to a daily frequency to keep the betas timely, which is important because betas of individual commodities vary quite dramatically over time (Bakshi et al. (2015)). 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 presents a 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 prices of risk for the factors of interest, their Shanken

[23]The composition of the sectors (Energy, Meats, Metals, Grains, Oilseeds, Softs, and Industrial Materials) can be found in Table IA.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.

[24]Rolling window betas automatically deal 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.

(1992) t-statistics, 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 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 translates to a Sharpe ratio of about 0.85. This estimate is close to the average return of the basis-momentum factor and thus satisfies the reality check for the risk-price of traded factors proposed in, e.g., Lewellen et al. (2010). 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 IA.10 of the Internet Appendix).

We conclude that a parsimonious two-factor model, combining basis-momentum with an average commodity market factor, provides an excellent cross-sectional fit compared to larger benchmark models, because exposure to a basis-momentum factor is a key determinant of cross-sectional variation in expected commodity returns. Figure 5 presents scatter plots of average returns versus model-predicted returns and confirms that average nearby and spreading returns line up relatively well with exposures in our two-factor model.

4.3 The basis-momentum factor and the price of volatility and liquidity risks

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.[25] 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 control for exposure to basis-momentum and we see that this factor largely drives out volatility, leaving only a small and insignificant price of volatility risk. We caution to not interpret these joint 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

[25]Table IA.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.

because it mimicks priced volatility risk. This general conclusion is further supported in Table IA.12 of the Internet Appendix, which shows that stock market volatility risk is priced similarly to commodity market volatility risk.

4.3.1 Basis-momentum, volatility, and liquidity

The fact that basis-momentum is strongly linked to volatility does not necessarily imply that volatility itself is the only state variable driving expected return variation. More likely, volatility also proxies for underlying state variables that drive the various dimensions of liquidity that are relevant for the ability of speculators and financial intermediaries to clear the market.[26] Following previous work, we provide some tentative evidence using the TED spread ($ILLIQ_{TED}$) as a simple proxy for funding illiquidity (see, e.g., Brunnermeier et al. (2009), Koijen et al. (2015) and Bakshi et al. (2015)) and the measure of Amihud (2002) aggregated across commodities ($ILLIQ_{AMI}$) as a proxy for market illiquidity (see Section 2.2). The idea is that times of illiquidity are plausibly associated to volatility and thus widening imbalances of supply and demand within and across commodity futures curves.

Table 12 tests whether innovations (i.e., first-differences) in $ILLIQ_{TED}$ and $ILLIQ_{AMI}$ are priced among commodity-portfolios sorted on basis-momentum, basis, and momentum. We find that both capture a significant negative price of risk when included next to the average commodity market factor, yielding an adequate R^2 of around 0.67 for these two-factor models. However, both illiquidity risk-prices are considerably smaller economically and insignificant when controlling for basis-momentum or volatility risk. These findings are consistent with the idea that volatility also proxies for various dimensions of liquidity and thus our hypothesis that basis-momentum returns are driven by the tight link between volatility and liquidity in the form of maturity-specific price pressure.

[26]These drivers include tightness of margin constraints, value-at-risk limits, recent returns of and capital devoted to commodity futures strategies, liquidity spillovers from other markets, and others.

5 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 important asset pricing implications. First, basis-momentum is the best known time series and cross-sectional predictor of nearby and spreading returns in commodity markets. The basis-momentum effect is maturity-specific, follows from predictability of roll returns (not appreciation of spot commodity prices), and exists also in currencies and stock indexes. Consequently, basis-momentum is unlikely to be driven by storage or inventory dynamics, but is consistent with maturity-specific price pressure. Consistent with the broader association between liquidity (in this case through price pressure) and volatility, we show that basis-momentum returns are increasing in volatility and exposed to volatility risk. In line with this finding, we find that exposure to a basis-momentum factor is priced, even after controlling for recently proposed commodity factors. A parsimonious two-factor model, including an average commodity market factor and the basis-momentum factor, does an excellent job explaining cross-sectional variation in nearby and spreading returns. Finally, the basis-momentum effect largely represents compensation for volatility and liquidity risk, which we show to be priced much more broadly in commodity markets than was previously known in the literature.

Our results are important for investors, because the recent financialization of commodity markets has inspired large and increasingly active institutional investment in commodities. We conclude that basis-momentum is key to understanding the variation of commodity prices and thus a crucial input for the models of empiricists and theorists alike. Future work is warranted to find the precise economic drivers of hedger's versus speculator's investment decisions that determine the separate components of basis-momentum: 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.

Appendix Decomposing nearby and spreading returns

We define 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, $y_t^{T_n}$:

$$F_t^{T_n} = S_t \exp\left(T_n \times y_t^{T_n}\right). \tag{A.1}$$

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 the first-nearby return uses the end of the month spot price. The conclusions can be generalized if this is not the case. We continue in logs, denoted by small letters.

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

$$E_t[r_{s,t+1}] = E_t[s_{t+1} - s_t] = \pi_{s,t} + y_t^1. \tag{A.2}$$

It is natural to decompose the spot return into a premium and a component related to expected price appreciation, as 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,

$$T_n \times y_t^{T_n} = y_t^1 + (T_n - 1)E_t[y_{t+1}^{T_n - 1}] + \pi_{y,t}^{T_n}. \tag{A.3}$$

The expected return from an investment in the first-nearby futures contract delivers the spot premium:

$$E_t[r_{fut,t+1}^1] = E_t[s_{t+1} - f_t^1] = E_t[s_{t+1} - s_t - y_t^1] = \pi_{s,t}. \tag{A.4}$$

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 an investment in the second-nearby futures contract equals:

$$E_t[r_{fut,t+1}^{T_2}] = E_t[f_{t+1}^{T_2-1} - f_t^{T_2}] = E_t[(s_{t+1} - s_t) + (y_{t+1}^{T_2-1} - T_2 y_t^{T_2})] \tag{A.5}$$

$$= (y_t^1 + \pi_{s,t}) - (y_t^1 + \pi_{y,t}^{T_2}) = \pi_{s,t} - \pi_{y,t}^{T_2}, \tag{A.6}$$

such that

$$E_t[r_{fut,t+1}^{spread}] = E_t[r_{fut,t+1}^1] - E_t[r_{fut,t+1}^2] = \pi_{y,t}^{T_2}. \tag{A.7}$$

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:

$$E_t[r_{fut,t+1}^1] = E_t[r_{fut,t+1}^{1,spot}] + E_t[r_{fut,t+1}^{1,roll}] = (\pi_{s,t} + y_t^1) + (-y_t^1), \tag{A.8}$$

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. We do not decompose the expected spreading return, because it does not contain a spot return component. 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. For the same reason, we do not decompose returns of farther-from-expiring contracts.

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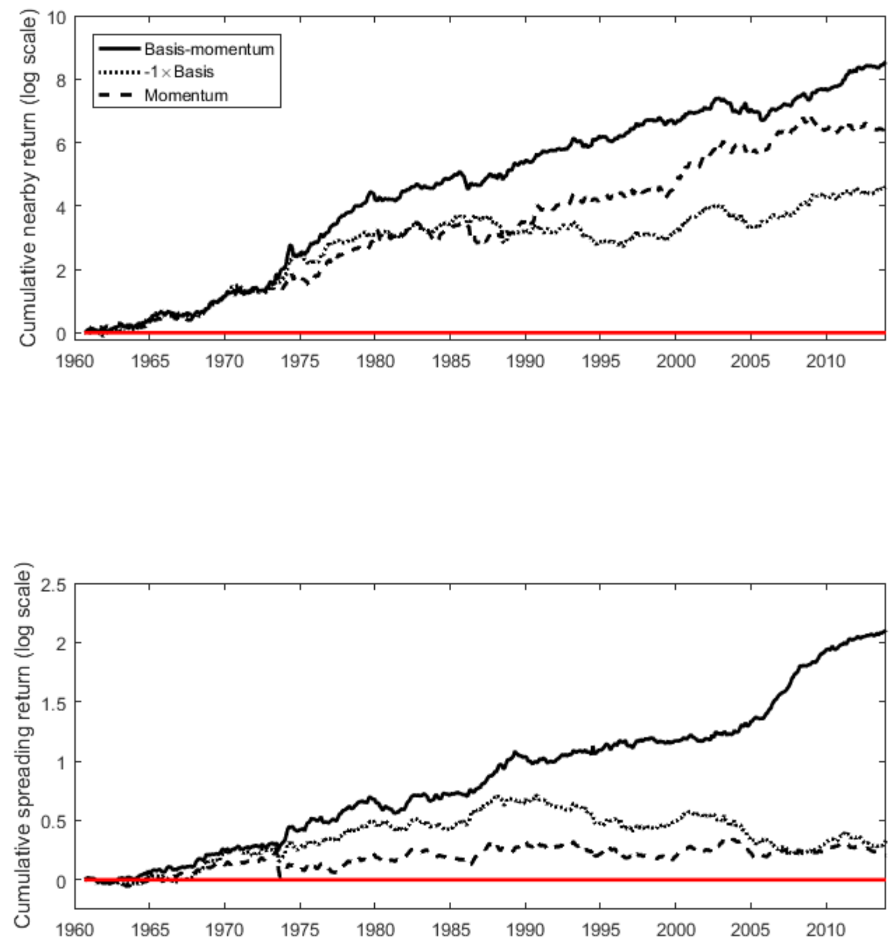

Figure 1: Cumulative returns on basis-momentum, basis, and momentum strategies
This figure presents cumulative nearby (top) and spreading (bottom) returns (on a log scale) for the High4-minus-low4 basis-momentum, basis, and momentum portfolios. The High4 and Low4 portfolios, respectively, contain the top four and bottom four commodities (out of 21) from a sort on each of the respective signals. For the sake of comparison, we present the negative of the returns on the basis strategy. The sample period is August 1960 to February 2014.

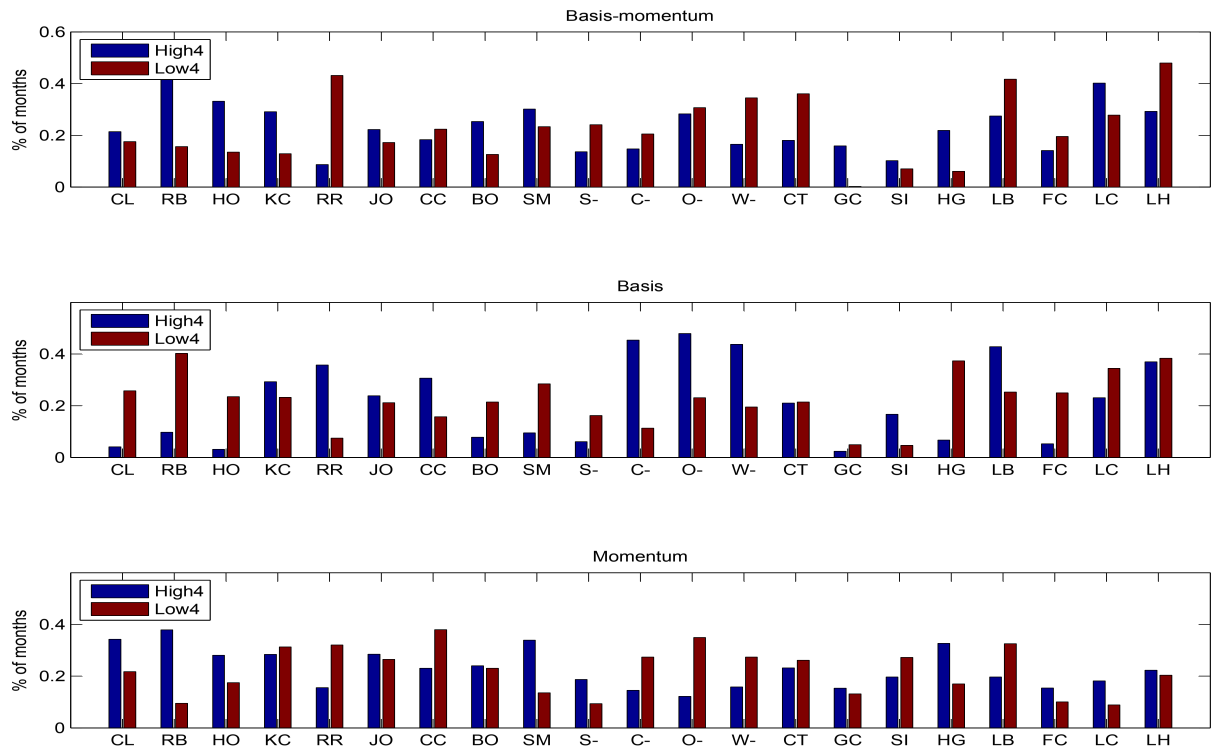

Figure 2: Composition of High4 and Low4 portfolios in commodity sorts
This figure presents the fraction of months in which a given commodity (see symbols in Table IA.1) is either among the top four (blue) or bottom four (red) commodities ranked on the three signals of interest: basis-momentum, basis, 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.

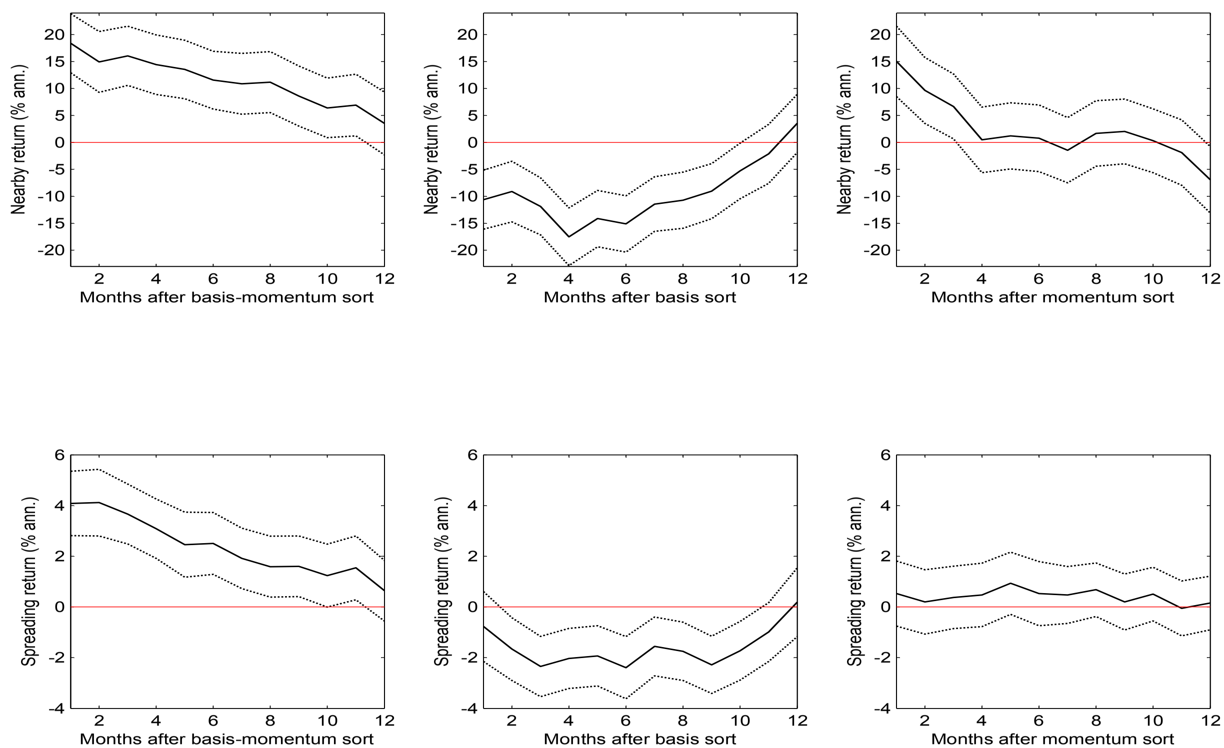

Figure 3: Nearby and spreading returns up to one year after portfolio formation
This figure presents average nearby (top) and spreading (bottom) returns (in annualized %) for the High4-minus-Low4 basis-momentum, basis, and momentum portfolios up to one year after portfolio formation. That is, with the 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.

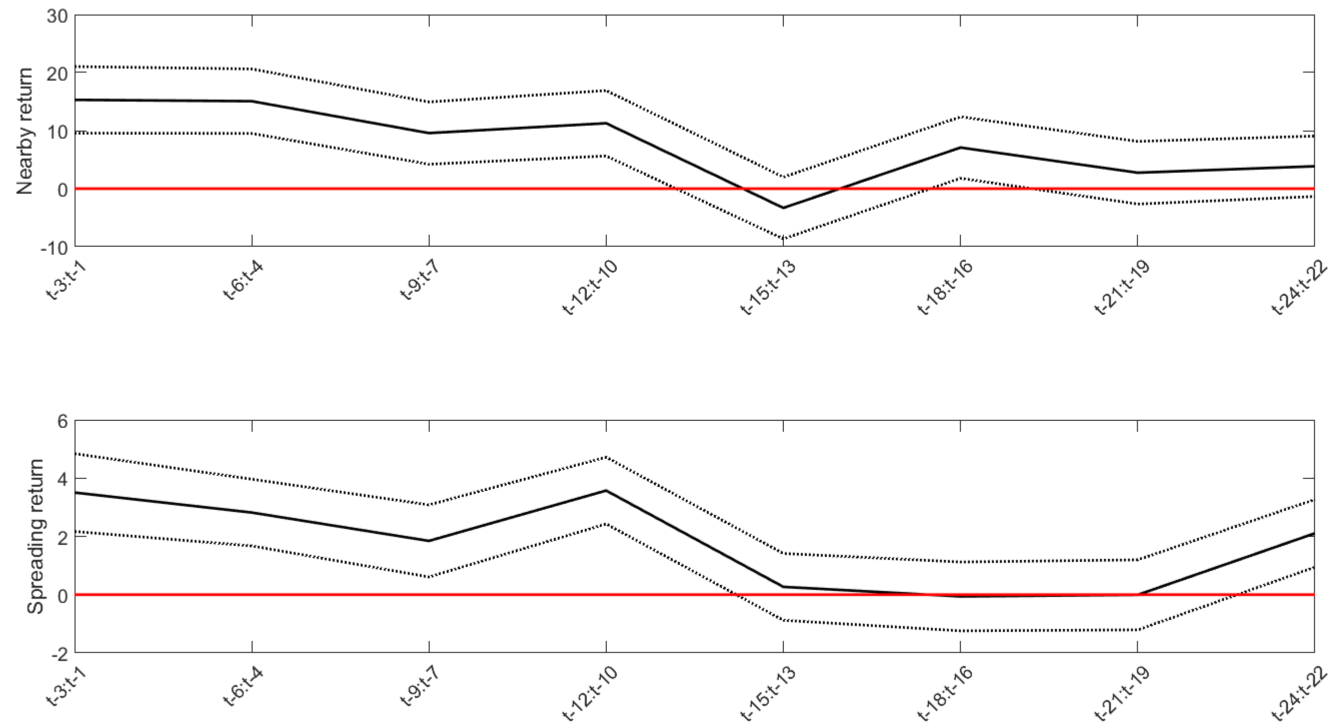

Figure 4: Basis-momentum returns over various ranking periods
This figure presents average nearby (top) and spreading (bottom) returns (in annualized %, plus two standard errors bands) for the High4-minus-Low4 basis-momentum portfolio ranking 21 commodities on basis-momentum calculated using quarterly first-nearby and second-nearby returns. There are a total of eight quarterly ranking periods from two years to one-month before portfolio formation. The sample period is August 1960 to February 2014.

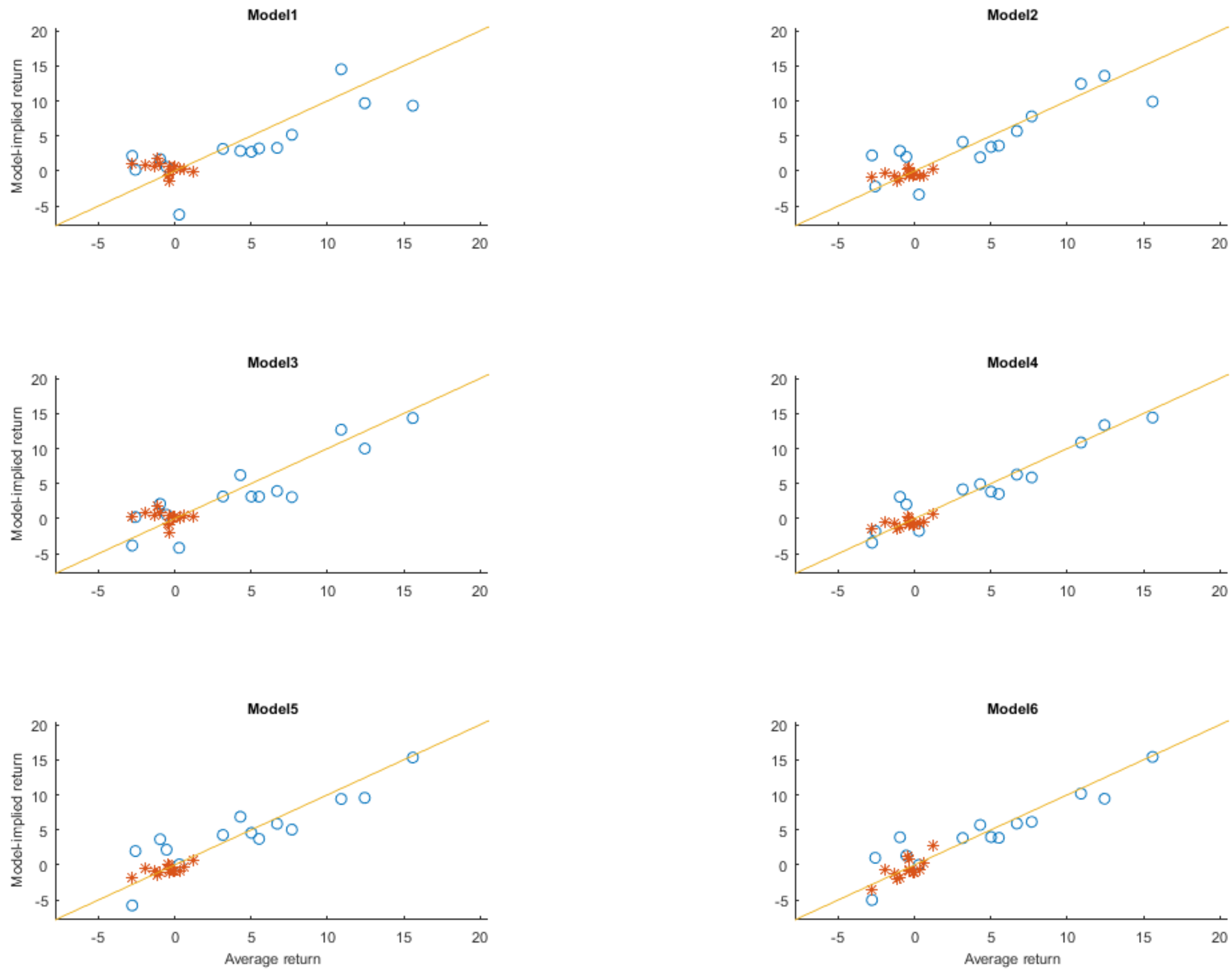

Figure 5: Model-implied expected returns versus historical average returns
This figure presents scatter plots of model-implied expected returns versus historical average returns. The model-implied returns are calculated using the six models analyzed in Table 10. The test assets are nearby returns (circles) and spreading returns (crosses) of portfolios sorted on basis-momentum, basis, momentum, and sector. 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 second subsample 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: 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 ($R^{T_1}_{fut,i,t+1}$ and $R^{T_1}_{fut,i,t+1} - R^{T_2}_{fut,i,t+1}$) of 21 commodities on lagged characteristics (see Equations (6) and (7)). 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. 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 momentum and second-nearby momentum ($M^{T_2}_{i,t}$). In the right block of results we regress futures returns on curvature and change in slope (see Section 1.2).

	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 3: Double sorts on basis-momentum and control variables

This table presents average nearby (Panel A) and spreading (Panel B) returns when we double sort commodities into 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); storability (splitting the sample into 17 "less" storable commodities and 15 "more" storable commodities); 12-month first-nearby volatility (split at the median); Amihud (2002) illiquidity (split at the median); and, finally, hedging and spreading pressure (split at the median, see also the definitions in Section 2.1). 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 (using only those months where we have at least 8 commodities with available data) as well as a sample from 1986-02 to 2012-01, dictated by availability of CFTC position data.

Table 3 continued

		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							
Basis-momentum	High	14.01	(5.32)						
	Low	-3.13	(-1.35)						
	Diff	17.14	(7.60)						
Basis	Contango	1.48	(0.66)	10.14	(3.67)	-3.94	(-1.65)	14.08	(5.48)
	Backwardation	11.11	(3.84)	14.48	(4.17)	0.31	(0.10)	14.17	(3.63)
	Diff	-9.62	(-3.85)	-4.34	(-1.25)	-4.25	(-1.42)		
12-Month basis	Contango	1.47	(0.63)	8.87	(2.84)	-3.71	(-1.52)	12.58	(4.32)
	Backwardation	8.98	(2.98)	15.31	(4.39)	-1.06	(-0.32)	16.37	(3.90)
	Diff	-7.50	(-2.90)	-6.45	(-1.76)	-2.65	(-0.82)		
Momentum	Winners	9.21	(3.47)	15.20	(5.13)	-0.45	(-0.15)	15.65	(4.69)
	Losers	1.20	(0.52)	11.49	(3.55)	-4.37	(-1.76)	15.86	(5.02)
	Diff	8.01	(3.49)	3.71	(1.15)	3.92	(1.21)		
Storage	More storable	6.45	(2.67)	15.47	(4.58)	-1.49	(-0.54)	16.96	(4.86)
	Less storable	3.99	(1.62)	13.16	(4.37)	-4.28	(-1.56)	17.44	(6.04)
	Diff	2.45	(1.12)	2.31	(0.67)	2.79	(0.99)		
Volatility	High	4.94	(1.76)	15.79	(4.43)	-5.92	(-1.93)	21.71	(6.05)
	Low	4.97	(2.40)	11.93	(4.46)	-1.34	(-0.59)	13.27	(5.00)
	Diff	-0.03	(-0.01)	3.86	(1.16)	-4.58	(-1.62)		
Amihud	Illiquid	5.76	(2.51)	17.58	(5.18)	-4.57	(-1.68)	22.15	(6.19)
	Liquid	4.26	(1.75)	11.24	(3.92)	-1.81	(-0.69)	13.05	(4.83)
	Diff	1.51	(0.83)	6.34	(2.10)	-2.75	(-1.07)		
		CFTC data sample from 1986-02 to 2012-01							
Hedging pres.	High	2.72	(1.09)	7.99	(2.30)	-0.63	(-0.24)	8.62	(2.53)
	Low	3.81	(1.33)	12.58	(3.90)	-6.42	(-1.81)	19.01	(5.25)
	Diff	-1.09	(-0.45)	-4.59	(-1.35)	5.79	(1.74)		
Spreading pres.	High	1.31	(0.52)	8.98	(2.76)	-4.38	(-1.52)	13.35	(3.93)
	Low	5.04	(1.78)	11.32	(3.34)	-1.72	(-0.53)	13.04	(3.68)
	Diff	-3.74	(-1.56)	-2.34	(-0.72)	-2.65	(-0.81)		

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

Table 3 continued

		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)
Panel B: Average spreading returns ($R^{T_1}_{fut,p,t+1} - R^{T_2}_{fut,p,t+1}$)									
Full sample									
Basis-momentum	High	0.96	(2.63)						
	Low	-2.08	(-7.10)						
	Diff	3.04	(7.07)						
Basis	Contango	-0.61	(-2.99)	0.59	(2.10)	-1.48	(-5.50)	2.07	(5.58)
	Backwardation	-0.70	(-1.27)	0.49	(0.73)	-3.43	(-4.83)	3.92	(4.27)
	Diff	0.09	(0.17)	0.10	(0.14)	1.95	(2.67)		
12-Month basis	Contango	-1.17	(-4.63)	0.43	(0.92)	-2.02	(-6.42)	2.45	(4.48)
	Backwardation	0.23	(0.44)	1.13	(1.75)	-1.52	(-2.77)	2.65	(3.36)
	Diff	-1.40	(-2.52)	-0.70	(-0.90)	-0.50	(-0.80)		
Momentum	Winners	-0.42	(-1.01)	0.94	(1.72)	-2.24	(-4.16)	3.17	(4.68)
	Losers	-0.82	(-3.08)	1.06	(2.12)	-1.87	(-5.79)	2.93	(5.10)
	Diff	0.40	(0.83)	-0.13	(-0.17)	-0.37	(-0.63)		
Storage	More storable	-0.36	(-0.99)	1.62	(3.03)	-1.97	(-4.32)	3.59	(5.30)
	Less storable	-0.81	(-2.55)	0.45	(0.94)	-2.12	(-5.75)	2.57	(4.85)
	Diff	0.45	(0.96)	1.18	(1.73)	0.16	(0.28)		
Volatility	High	-0.65	(-1.63)	0.90	(1.46)	-2.11	(-4.66)	3.01	(4.33)
	Low	-0.64	(-2.38)	1.10	(2.52)	-2.14	(-6.24)	3.25	(6.05)
	Diff	-0.01	(-0.02)	-0.20	(-0.28)	0.03	(0.06)		
Amihud	Illiquid	-0.46	(-1.40)	1.39	(2.52)	-2.19	(-5.12)	3.58	(5.16)
	Liquid	-0.79	(-2.68)	0.31	(0.69)	-1.85	(-5.37)	2.16	(4.04)
	Diff	0.33	(0.87)	1.08	(1.64)	-0.34	(-0.69)		
CFTC data sample from 1986-02 to 2012-01									
Hedging pres.	High	-1.46	(-3.85)	0.13	(0.25)	-2.36	(-4.78)	2.49	(3.65)
	Low	-1.15	(-2.98)	0.45	(0.85)	-3.05	(-5.99)	3.49	(5.17)
	Diff	-0.31	(-0.61)	-0.32	(-0.45)	0.69	(1.05)		
Spreading pres.	High	-2.26	(-5.87)	0.05	(0.09)	-3.93	(-7.84)	3.99	(5.61)
	Low	-0.42	(-1.15)	0.56	(1.12)	-1.49	(-3.09)	2.04	(3.14)
	Diff	-1.84	(-3.86)	-0.51	(-0.72)	-2.45	(-3.88)		

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			
Sorting variable		$R^{T_2}_{fut,s}$	$R^{T_2}_{fut,s} - R^{T_3}_{fut,s}$	$R^{T_3}_{fut,s}$	$R^{T_3}_{fut,s} - R^{T_4}_{fut,s}$
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		
$BM^{2,3}_t\|BM_t$	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
$BM^{3,4}_t\|BM_t$	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. 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 (15), (16), and (17)). To be precise, we count the number of positive and negative coefficients (η_{BM}, η_{BM}^{spot}, and η_{BM}^{roll}) 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 $X_{i,t}$			
# $\eta_X^{spot} > 0$	10	19	3
# $t_{\eta_X^{spot}} > 1.65$	1	15	0
# $\eta_X^{spot} \leq 0$	11	2	18
# $t_{\eta_X^{spot}} \leq -1.65$	2	0	6
Panel C: Roll returns ($r^{roll}_{fut,i,t+1:t+T_1}$) on $X_{i,t}$			
# $\eta_X^{roll} > 0$	19	0	20
# $t_{\eta_X^{roll}} > 1.65$	18	NA	19
# $\eta_X^{roll} \leq 0$	2	21	1
# $t_{\eta_X^{roll}} \leq -1.65$	0	NA	0

Table 7: Currencies and stock indexes sorted on basis-momentum

This table presents unconditional performance measures for currencies (Panel A) and stock indexes (Panel B) sorted on basis-momentum, basis, and momentum. (Section 1 of the Internet Appendix contains a description of the data and variable definitions.) The currency 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. The stock index portfolios are also equal-weighted and contain a total of 12 stock indexes with futures prices available from the CRB or in Datastream. Nearby and spreading currency forward returns are defined as: $R^1_{cur,t+1} = S_{t+1}/F^1_t$ (the return from buying a currency at the one month forward price) and $R^{spread}_{cur,t+1} = R^1_{cur,t+1} - F^1_{t+1}/F^2_t$ (which subtracts from the nearby return the return from closing a two-month currency forward contract one month after initiation). Nearby and spreading returns for the stock indexes are defined analogous to commodities, as a long position in the first-nearby futures contract and a spreading position that is long the first-nearby and short the second-nearby contract. The High4 and Low4 portfolio contain the top and bottom four ranked currencies or stock indexes, respectively, whereas the Mid portfolio contains all remaining assets, which number is time-varying. The currency sample period runs from April 1997 to August 2015, the stock index sample period runs from August 2002 to December 2014, both dictated by data availability.

	Basis-momentum				Basis	Momentum
	High4	Mid	Low4	High4-Low4	High4-Low4	High4-Low4
			Panel A: Currencies			
			Nearby returns ($R^1_{cur,t+1}$)			
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
			Spreading returns ($R^{spread}_{cur,t+1}$)			
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
			Panel B: Stock indexes			
			Nearby returns ($R^{T_1}_{stock,t+1}$)			
Avg. Ret.	9.20	7.28	4.76	4.45	-2.60	-2.00
(t)	(1.64)	(1.31)	(0.86)	(2.01)	(-1.13)	(-0.77)
Sharpe	0.47	0.38	0.25	0.58	-0.33	-0.22
			Spreading returns ($R^{T_1}_{stock,t+1} - R^{T_2}_{stock,t+1}$)			
Avg. Ret.	0.88	0.24	-0.14	1.01	1.15	-1.02
(t)	(1.83)	(0.90)	(-0.41)	(1.82)	(1.92)	(-1.83)
Sharpe	0.53	0.26	-0.12	0.53	0.55	-0.53

Table 8: Basis-momentum and volatility (risk)

This table presents results from various tests that link basis-momentum 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. Panel A presents coefficient estimates, υ_{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. In this regression, both variance series are winsorized at the 1%-level and standardized. Panel B presents average returns conditioning on whether the lagged variance measures are above their historical median ("high volatility months") or not ("normal months"). We use the first 60 months of the sample as burn-in period for the estimation of the medians. Panel C presents coefficient estimates, ν_{var}, from time series regressions of nearby and spreading returns on contemporaneous monthly innovations in the variance series. We perform this regression over the full sample as well as for those months where the drawdown of the High4-minus-Low4 portfolio is below median, with drawdown defined as $D_{t+1} = \sum_{s=1}^{t+1} r_{fut,H4-L4,t+1}^{T_1} - \max_{u \in \{1,\ldots,t+1\}} \sum_{s=1}^{u} r_{fut,H4-L4,t+1}^{T_1}$ for nearby returns and analogously for spreading returns. Standard errors are Newey-West with lag length k (1) in Panel A (B and C). The sample period is August 1960 to February 2014.

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

	Nearby returns ($R_{fut,p,t+1:t+k}^{T_1}$)						Spreading returns ($R_{fut,p,t+1:t+k}^{T_1} - R_{fut,p,t+1:t+k}^{T_2}$)					
k	1	1	1	1	6	12	1	1	1	1	6	12
	High4	Mid	Low4	H4-L4	H4-L4	H4-L4	High4	Mid	Low4	H4-L4	H4-L4	H4-L4
υ_{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
υ_{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: Basis-momentum in high volatility vs. normal months

	High4-Low4 nearby returns			High4-Low4 spreading returns		
	High Vol.	Normal	Diff.	High Vol.	Normal	Diff.
Avg. Ret.	23.81	10.82	12.99	5.34	2.61	2.73
(t)	(5.86)	(2.69)	(2.20)	(5.72)	(2.74)	(1.99)
Sharpe	1.06	0.63	0.42	1.03	0.64	0.39

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

	Nearby returns ($R_{fut,p,t+1}^{T_1}$)					Spreading returns ($R_{fut,p,t+1}^{T_1} - R_{fut,p,t+1}^{T_2}$)				
	High4	Mid	Low4	H4-L4	H4-L4 Drawdowns	High4	Mid	Low4	H4-L4	H4-L4 Drawdowns
ν_{var}^{mkt}	-7.78	-2.13	0.87	-8.65	-5.99	-0.18	-0.57	-0.14	-0.03	-2.01
(t)	(-1.83)	(-0.54)	(0.19)	(-3.14)	(-1.78)	(-0.46)	(-2.56)	(-0.35)	(-0.05)	(-1.69)
ν_{var}^{avg}	-1.68	-0.12	1.14	-2.82	-3.44	-0.02	-0.10	0.14	-0.16	-0.76
(t)	(-1.12)	(-0.10)	(0.84)	(-2.63)	(-2.38)	(-0.11)	(-1.12)	(0.78)	(-0.62)	(-3.11)

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 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 factor 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 on their full sample exposures. The portfolios include 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). 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 rolling one-year 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: 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]

Table 12: Cross-sectional asset pricing tests with illiquidity risk

This table conducts portfolio-level cross-sectional regressions to determine the price of illiquidity risk in commodity markets and its relation to the price of basis-momentum and volatility risk. We consider two measures of illiquidity. The TED spread proxies for funding illiquidity and is measured as the 3-month interbank LIBOR interest rate minus the 3-month US t-bill rate. An aggregate commodity market Amihud-measure proxies for market illiquidity. This measure is calculated as follows using daily first- and second-nearby returns ($R^{T_n}_{fut,i,d}$) and dollar volume ($Vol^{T_n}_{i,d}$)). For each commodity, we calculate a backward-looking annual average of the daily measure: $R^{T_n}_{fut,i,d}/Vol^{T_n}_{i,d}$. We then aggregate over all commodities i by taking separately the median of first- and second-nearby contracts to deal with outliers and the fact that first-nearby contracts are typically more liquid. Then, the aggregate commodity-market Amihud-measure is the average of the first- and second-nearby Amihud-measures. To measure risk, we take the first-differences in these illiquidity series, denoted $ILLIQ_{TED}$ and $ILLIQ_{AMI}$ (we take log-differences for the Amihud-serie to correct for the fact that liquidity is increasing over time). Models 1 and 2 are two-factor models that include the illiquidity measures next to the average nearby factor ($R^{nearby}_{AVG,t+1}$). Models 3 and 4 control for the basis-momentum factors. Models 5 to 8 control for non-traded innovations in aggregate and average commodity market variance, respectively, i.e., Δvar^{mkt}_{t+1} and Δvar^{avg}_{t+1}. These tests regress average nearby and spreading returns of commodity portfolios sorted on basis-momentum, basis, and momentum (the High4, Mid, and Low4 portfolio from these sorts) 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. The sample period is February 1986 to February 2014, dicated by data availability.

	γ_0	γ^{nearby}_{AVG}	γ^{nearby}_{BM}	γ^{mkt}_{var}	γ^{avg}_{var}	$\gamma_{ILLIQ_{TED}}$	$\gamma_{ILLIQ_{AMI}}$	R^2 $MAPE$	$MAPE_{nearby}$ $MAPE_{spread}$
Model 1	-1.84	5.56				-3.06		0.68	[2.87]
	(-3.32)	(2.27)				(-1.91)		[2.00]	[1.14]
Model 2	-0.80	6.16					-0.89	0.67	[3.44]
	(-1.18)	(2.50)					(-2.28)	[2.16]	[0.88]
Model 3	-1.68	5.20	18.21			-0.82		0.87	[1.63]
	(-4.62)	(2.20)	(4.31)			(-0.78)		[1.24]	[0.85]
Model 4	-1.21	5.36	18.55				-0.39	0.90	[1.65]
	(-2.47)	(2.27)	(4.14)				(-1.43)	[1.20]	[0.75]
Model 5	-1.77	4.92		-0.12		0.05		0.85	[1.79]
	(-3.12)	(2.02)		(-2.46)		(0.03)		[1.54]	[1.29]
Model 6	-1.49	5.12			-0.28	-0.72		0.78	[2.34]
	(-3.05)	(2.12)			(-2.37)	(-0.45)		[1.66]	[0.99]
Model 7	-1.22	5.17		-0.09			-0.42	0.87	[1.75]
	(-2.05)	(2.17)		(-2.21)			(-1.32)	[1.35]	[0.94]
Model 8	-0.95	5.30			-0.22		-0.47	0.83	[2.42]
	(-1.57)	(2.22)			(-1.95)		(-1.43)	[1.56]	[0.71]

Internet Appendix

This internet appendix contains supplementary material and results for "Basis-momentum in the futures curve and volatility risk."

1 Stock index and currency data

This section presents the data we use in our tests for currencies and stock indexes. To be consistent with a large body of literature on currencies, the currency return data is constructed using forward exchange rates. Our 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, Iceland, 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 define currency basis-momentum, basis, and momentum as follows

$$BM_{i,t}^{cur} = \prod_{s=t-2}^{t} (S_{t+1}/F_t^1) - \prod_{s=t-2}^{t} (F_{t+1}^1/F_t^2), \tag{IA.1}$$

$$B_{i,t}^{cur} = F_t^1/S_t - 1, \tag{IA.2}$$

$$M_{i,t}^{cur} = \prod_{s=t-2}^{t} (S_{t+1}/F_t^1) - 1, \tag{IA.3}$$

where S_{t+1}, F_{t+1}^1, and F_{t+1}^2 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.

We largely follow Moskowitz et al. (2012) and Koijen et al. (2015) in collecting a sample of twelve stock indexes with futures data available from the CRB or in Datastream: United States (S&P500), United Kingdom (FTSE), Germany (DAX), Italy (MIB-mini), Japan (TOPIX), Australia (ASX), Netherlands (AEX), France (CAC40), Finland (OMX), Spain (IBEX-mini), Switzerland (SMI), and Hong Kong (Hang Seng). We construct first- and second-nearby stock index futures returns following the same exact procedure as described in Section 1.1 for commodities. We also define basis-momentum, basis, and momentum as described in in Section 1.2. Most stock indexes trade only contracts with maturities in March, June, September, or December, especially early on in the sample. To be consistent over the full sample period and across indexes, we use only these maturities. We check that the correlation between each first-nearby stock index futures returns and the corresponding cash index is almost perfect. For our sort, we use all months with at least eight stock indexes with available first- and second-nearby data. This leaves us with a final sample of 144 months (out of the available 149 months) over the period from August 2002 to December 2014.

2 Additional empirical evidence

This section presents a number of robustness checks for our empirical evidence.

Table IA.1: Overview of commodity futures contracts

This table presents the sample of first- and second-nearby futures returns ($R^{T_1}_{fut,i,t+1}$ and $R^{T_2}_{fut,i,t+1}$) for 32 commodities, 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		$R^{T_1}_{fut,i,t+1}$		$R^{T_2}_{fut,i,t+1}$	
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 IA.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 second subsample 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 IA.3: Pooled regressions of commodity-level returns on lagged characteristics (32 commodities)

This table is similar to Table 2 in the paper, but uses the larger set of 32 commodities. 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 32 commodities on lagged characteristics (see Equations (6) and (7)). 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. 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 momentum and second-nearby momentum ($M^{T_2}_{i,t}$). In the right block of results we regress futures returns on curvature and change in slope (see Section 1.2).

	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)
$\lambda_M^{T_2}$	-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

Table IA.4: 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 IA.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. There is one observation less for the case of basis in Panel B, because gold is always in contango.

Panel A: Futures return on lagged basis-momentum 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 IA.4 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 IA.5: Basis-momentum across the futures curve (32 commodities)
This table is similar to Table 4 of the paper, but uses the larger set of 32 commodities. 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			
Sorting variable		$R^{T_2}_{fut,s}$	$R^{T_2}_{fut,s} - R^{T_3}_{fut,s}$	$R^{T_3}_{fut,s}$	$R^{T_3}_{fut,s} - R^{T_4}_{fut,s}$
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
$BM^{2,3}_t$	Avg. Ret.	16.79	2.47		
	(t)	(6.39)	(4.07)		
	Sharpe	0.87	0.56		
$BM^{2,3}_t\|BM_t$	Avg. Ret.	12.17	2.79		
(329 Months)	(t)	(3.35)	(3.16)		
	Sharpe	0.64	0.60		
$BM^{3,4}_t$	Avg. Ret.			10.32	0.87
	(t)			(4.07)	(1.67)
	Sharpe			0.56	0.23
$BM^{3,4}_t\|BM_t$	Avg. Ret.			12.66	0.92
(436 Months)	(t)			(3.95)	(1.38)
	Sharpe			0.66	0.23

Table IA.6: 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 IA.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 (15), (16), and (17)). 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.

	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 IA.7: Does volatility predict basis-momentum portfolio returns? WLS instead of OLS.

This table presents coefficient estimates from time series regressions of High4-minus-Low4 basis-momentum portfolio returns (compounded over horizons of $k = \{1, 6, 12\}$ months) on lagged variance (aggregate and average commodity market variance: var_t^{mkt} and var_t^{avg}). Relative to Panel A of Table 8 of the paper, the only difference is that we estimate the predictive regressions by WLS instead of OLS. Weighting each nearby ($R^{T_1}_{fut,H4-L4,t+1:t+k}$) and spreading ($R^{T_1}_{fut,H4-L4,t+1:t+k} - R^{T_2}_{fut,H4-L4,t+1:t+k}$) return observation by the inverse of conditional volatility leads to more efficient estimates. We use the standard deviation of returns from $t-11$ to t as a simple proxy for conditional volatility in month $t+1$. Standard errors are Newey-West with lag length k. The sample period is August 1960 to February 2014.

	Nearby returns			Spreading returns		
k	1	6	12	1	6	12
$v^{mkt}_{var,WLS}$	9.31	8.64	7.09	1.16	1.35	1.24
(t)	(2.45)	(2.89)	(2.17)	(1.55)	(2.74)	(3.75)
R^2	0.03	0.09	0.10	0.03	0.12	0.14
$v^{avg}_{var,WLS}$	9.09	7.35	6.45	1.42	1.45	1.39
(t)	(2.90)	(2.92)	(2.23)	(1.93)	(3.02)	(3.75)
R^2	0.03	0.09	0.10	0.03	0.13	0.16

Table IA.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 High4-minus-Low4 basis- and momentum-sorted portfolios to volatility. Panel A presents coefficient estimates, v_{var}, from time series regressions of basis and 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, ν_{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 and momentum returns?

	Nearby returns ($R^{T_1}_{fut,H4-L4,t+1:t+k}$)				Spreading returns ($R^{T_1}_{fut,H4-L4,t+1:t+k} - R^{T_2}_{fut,H4-L4,t+1:t+k}$)			
	Basis		Momentum		Basis		Momentum	
k	1	12	1	12	1	12	1	12
v^{mkt}_{var}	-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^{avg}_{var}	-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 basis and momentum returns exposed to volatility risk?

	Nearby returns ($R^{T_1}_{fut,H4-L4,t+1}$)		Spreading returns ($R^{T_1}_{fut,H4-L4,t+1} - R^{T_2}_{fut,H4-L4,t+1}$)	
	Basis	Momentum	Basis	Momentum
ν^{mkt}_{var}	5.78	-5.95	-0.20	-0.22
(t)	(2.41)	(-2.02)	(-0.27)	(-0.34)
ν^{avg}_{var}	2.60	-1.44	0.00	0.05
(t)	(2.02)	(-0.99)	(0.00)	(0.19)

Table IA.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 (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 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 IA.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. 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 factor 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 on their full sample exposures. The portfolios include 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). 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 IA.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 rolling one-year 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 IA.11: Cross-sectional asset pricing tests: Basis-momentum versus volatility risk (32 commodities)

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 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	-0.99	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]

Table IA.12: Cross-sectional asset pricing tests: Basis-momentum versus stock market volatility risk

This table is similar to Table 11 of the paper, and conducts portfolio-level cross-sectional regressions to test the relation between the pricing of basis-momentum and stock market volatility risk. We consider two models. The first model is a two-factor model including the average factor and non-traded innovations in stock market variance, measured as the sum of squared daily returns on the S&P500 (Δvar_{t+1}^{SP500}). In model two, we add the basis-momentum factor. 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_{AVG}^{nearby}	γ_{BM}^{nearby}	γ_{var}^{SP500}	R^2 $MAPE$	$MAPE_{nearby}$ $MAPE_{spread}$
Model 1	-1.08	5.15		-0.65	0.74	[2.75]
	(-2.41)	(2.68)		(-3.04)	[1.81]	[0.86]
Model 2	-1.03	5.43	19.67	-0.25	0.87	[1.89]
	(-3.53)	(2.95)	(6.41)	(-1.42)	[1.31]	[0.74]