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Basis-Momentum

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ABSTRACT

We introduce a return predictor related to the slope and curvature of the futures term structure: basis-momentum. Basis-momentum strongly outperforms benchmark characteristics in predicting commodity spot and term premiums in both the time series and the cross section. Exposure to basis-momentum is priced among commodity-sorted portfolios and individual commodities. We argue that basis-momentum captures imbalances in the supply and demand of futures contracts that materialize when the market-clearing ability of speculators and intermediaries is impaired, and that it represents compensation for priced risk. Our findings are inconsistent with alternative explanations based on storage, inventory, and hedging pressure.

In this paper, we introduce a characteristic derived from the futures term structure, which we refer to as "basis-momentum." Basis-momentum is directly observable ex ante and is the strongest predictor of commodity returns to date, in the cross section and time series as well as across maturities. A large literature studies stock and bond risk premiums along these dimensions. We show that exposure to a basis-momentum factor is priced in the broadest cross section of commodities studied to date. We further explore potential explanations and argue that the basis-momentum effect is most consistent with priced risk that derives from the role of speculators and financial intermediaries in commodity

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markets. These asset pricing implications are also important for practitioners because the recent financialization has induced large and increasingly active institutional investment in commodities.[1]

Basis-momentum is measured as the difference in momentum between first- and second-nearby futures strategies, and can be decomposed into average curvature and changes in the slope of the futures curve. Given that the futures curve is typically steeper on the short end, it is not surprising to find that curvature positively predicts both nearby returns and spreading returns (from a long-short position in both a nearby contract and a farther-from-expiring contract). Likewise, persistence in the steepening of the slope predicts nearby returns both in absolute terms and relative to farther-from-expiring returns.

As in bond markets, the dynamics of commodity futures curves are driven by three factors: level, slope, and curvature (see Karstanje, van der Wel, and van Dijk (2015)). Nevertheless, our evidence suggests that the basis-momentum factor is the single best predictor of returns. In a similar spirit, Cochrane and Piazzesi (2005) find that a single tent-shaped function of forward rates is the best predictor of bond returns. More recent work on the term structure incorporates this tent-shaped factor as an additional characteristic to be matched by the model, thus connecting the factor structure of expected returns and yields (see, for example, Cochrane and Piazzesi (2008), Xiong and Yan (2010), and Campbell, Sunderam, and Viceira (2016)).

Sorting 21 commodities since 1959, we find a large average annualized difference between the high and low basis-momentum portfolios of 18.38% ($t = 6.73$) in (first-) nearby returns and 4.08% ($t = 6.43$) in (first-nearby minus second-nearby) spreading returns.[2] These returns translate into Sharpe ratios of 0.9 and capture commodity spot and term premiums, respectively. In pooled regressions that control for systematic differences across commodities, a one-standard-deviation increase in basis-momentum predicts a large increase in annualized nearby (spreading) returns of 10.23% (2.29%). Benchmark predictors such as basis and momentum are considerably weaker in isolation and are subsumed by basis-momentum in joint tests.[3]

Additional tests show that both curvature and changes in slope contribute to basis-momentum predictability, but it is curvature that contributes the most. This finding is important because basis and momentum are not directly related to curvature. Also, the restriction imposed by basis-momentum, namely, that the difference between momentum measured at different points on the curve outperforms a single momentum measure is supported in the data.

[1] For recent work on financialization, see, for example, Tang and Xiong (2012), Cheng, Kirilenko, and Xiong (2015), Sockin and Xiong (2015), and Basak and Pavlova (2016).

[2] These returns are robust to using the estimates of transaction costs reported in Marshall, Nguyen, and Visaltanochoti (2012) and Bollerslev et al. (2016) as well as to limiting various subsamples.

[3] For empirical evidence on the basis (the difference between the futures and spot price) and momentum, see, for example, Moskowitz, Ooi, and Pedersen (2012), Yang (2013), Szymanowska et al. (2014), Bakshi, Gao, and Rossi (2017), and Koijen et al. (2018).

Finally, evidence from first- to fourth-nearby contract returns suggests that basis-momentum predictability is maturity-specific.

Documenting the strength of basis-momentum predictability across all of these different dimensions is our first contribution. Our second contribution is to a recent literature that constructs commodity factor pricing models, in the spirit of Fama and French (1993). We construct basis-momentum nearby and spreading factors. In time-series spanning regressions, the basis-momentum factors generate large alphas relative to the three-factor models of Szymanowska et al. (2014) and Bakshi, Gao, and Rossi (2017). These models include commodity market, basis, and momentum factors. We run asset pricing tests using as test assets the nearby and spreading returns of either a range of portfolios (sorted on characteristics and sectors) or individual commodities. We find that exposure to the basis-momentum nearby factor captures priced risk that is orthogonal to the benchmark factors. The basis-momentum risk premium is close to the sample average return of the factor and translates into a Sharpe ratio ranging from 0.55 to 0.85 (depending on the specification). In fact, a two-factor model that includes a commodity market factor and the basis-momentum nearby factor provides a cross-sectional fit that is similar to larger three- and four-factor models. In contrast to the two factors in this parsimonious model, we find that the pricing performance of additional factors is sensitive to the specification of the asset pricing test.

Our third and final contribution is in exploring the economic determinants of basis-momentum. We argue that the classical theories of storage (Kaldor (1939), Working (1949), and Deaton and Laroque (1992)), normal backwardation (Keynes (1930)), and hedging pressure (Cootner (1960, 1967)) are unlikely to explain the effect.[4] For storage, we present three results. First, the basis-momentum effect is similar for commodities with high or low inventory and storability. Second, basis-momentum predicts returns controlling for basis, momentum, and volatility, which are price-based measures of inventory risk (Gorton, Hayashi, and Rouwenhorst (2012)). Third, basis-momentum predicts returns of currencies as well as stock and bond indexes, that is financial assets that can be stored costlessly. Although stronger in commodities, the existence of an effect in other assets indicates that basis-momentum is of general interest in asset pricing. Looking at hedging pressure, we note that the principal ideas of Keynes and Cootner say little about maturity-specific effects. Moreover, basis-momentum is empirically robust to controlling for hedging pressure.

We also analyze explanations that rely on the market-clearing ability of speculators, and of financial intermediaries more generally. We show that basis-momentum predictability is substantially stronger when speculators have many spreading positions. Such "spreading pressure" also predicts commodity returns in isolation, which is a new result in the literature. The information

[4] The theory of storage assumes that holders of inventories receive a convenience yield that declines as inventory increases, and that futures prices are set through cost-of-carry arbitrage. Hedging pressure is a reinterpretation of the theory of normal backwardation and links futures risk premiums to the net demand of producers and consumers relative to speculators.

content of spreading pressure is consistent with the idea that volatility and liquidity play a role in explaining basis-momentum. Speculators might be averse to taking directional exposure in times of high volatility. Also, Kang, Rouwenhorst, and Tang (2016) argue that speculators' trades often involve taking liquidity, which in the case of spreading positions implies a differential price impact within the curve of a single commodity.

To investigate the relation between liquidity, volatility, and basis-momentum, we follow the approach of Brunnermeier, Nagel, and Pedersen (2008) and Nagel (2012), who similarly investigate the carry trade and short-term reversal strategies. Among others, Brunnermeier and Pedersen (2009) argue that when liquidity is tight, speculators become reluctant to take positions that clear the market, which increases volatility. Conversely, liquidity declines when fundamental volatility increases. Because our results suggest that commodity-specific volatility does not drive the basis-momentum effect, we test these ideas using measures of aggregate commodity-market volatility that are more relevant for speculators and financial intermediaries than hedgers (who typically trade in one or a few markets). Empirically, we find that nearby and spreading basis-momentum returns are increasing in lagged volatility. The evidence is therefore consistent with the interpretation that basis-momentum captures the returns to liquidity provision by speculators who absorb imbalances in the supply of and demand for futures contracts, with these returns increasing in volatility.

Inspired by the growing literature on volatility risk, we show that exposure to volatility shocks captures a negative price of risk in commodity markets, which implies that investors are willing to pay for insurance against increases in volatility. The estimated price of risk is −0.65 in Sharpe ratio, consistent with estimates from other asset classes and the basis-momentum strategy, which is negatively exposed to volatility.[5] Because volatility is subsumed by basis-momentum in a joint test, our evidence supports the interpretation that exposure to basis-momentum captures a premium because it exposes investors to priced volatility risk.

The above results do not necessarily imply that volatility is the only relevant state variable. 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 state variables is difficult because liquidity is multidimensional and unobservable (Brunnermeier, Nagel, and Pedersen (2008) and Nagel (2012)). We show, however that popular proxies for market and funding liquidity risk are priced in commodity markets and are again driven out by basis-momentum. Also, the basis-momentum effect is stronger for illiquid commodities.

Finally, we test whether basis-momentum is related to financial intermediary capital risk (Adrian, Etula, and Muir (2014) and He, Kelly, and Manela (2017)) and downside market risk (Lettau, Maggiori, and Weber (2014)). In isolation,

[5] See, for example, Ang et al. (2006) and Adrian and Rosenberg (2008) for stocks, and Lustig, Roussanov, and Verdelhan (2011) and Menkhoff et al. (2012) for currencies.

both risk factors are priced in our cross section of commodities, consistent with previous evidence from a range of asset classes. Our price-of-risk estimates for the financial intermediary factor of He, Kelly, and Manela (2017) are consistent with theories of leverage-constrained intermediaries, as in the frameworks of Brunnermeier and Pedersen (2009) and Adrian and Shin (2014). However, basis-momentum subsumes the pricing information in these risk factors in a joint test.

Overall, the basis-momentum effect is consistent with imbalances in the supply of and demand for futures contracts that materialize within and across futures curves when the market-clearing ability of speculators and financial intermediaries is impaired. Basis-momentum is risky because this strategy incurs losses when volatility and illiquidity suddenly increase and in low market return episodes. We show that these risk factors are priced much more broadly in commodity markets than was previously known, which represents a contribution to the literature that is independent of basis-momentum.[6]

I. Data and Variable Definitions

In this section, we describe our data and define the basis-momentum characteristic.

A. Commodity Futures Data and Returns

We collect data on exchange-traded, liquid commodity futures contracts from the Commodity Research Bureau (CRB). Part of this data set is used in Szymanowska et al. (2014) to study 21 commodity futures from 1986 to 2010. We extend this data set such that it starts in July 1959, when CRB data are first available, and ends in February 2014. We also add data for 11 commodities, including some large markets such as natural gas.

We calculate monthly excess returns on a fully collateralized futures position,

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

where $F^{T_n}_{t+1}$ is the end-of-month price of the n^{th}-nearby futures contract with expiration in month $t + T_n$. We follow Szymanowska et al. (2014) and restrict expiration to be after $t + 2$. This approach avoids holding contracts close to expiration, when unusual price and volume behavior sometimes occurs. Although our tests focus on the more liquid first- and second-nearby contracts ($n = 1, 2$), in robustness checks we use third- and fourth-nearby contracts ($n = 3, 4$).

[6] Bakshi, Gao, and Rossi (2017) and Koijen et al. (2018) show that volatility risk is priced in a cross section of basis portfolios. He, Kelly, and Manela (2017) show that financial intermediary risk is priced in a cross section of individual commodities in a relatively short sample over 2002 to 2012.

In the Appendix, we decompose expected futures returns into spot and term premiums. Analogous to the bond market, spot premiums are captured by a long position in the first-nearby contract, $R^{T_1}_{\text{fut},t+1}$. Henceforth, we denote this nearby return as $R^{\text{nb}}_{\text{fut},t+1}$. Term premiums are captured by a long-short position in the first-nearby contract and a farther-from-expiring contract. We use $R^{\text{spr}}_{\text{fut},t+1}$ to capture the (first-minus-second-nearby) spreading return, $R^{T_1}_{\text{fut},t+1} - R^{T_2}_{\text{fut},t+1}$. Table IA.I of the Internet Appendix presents summary statistics for these commodity returns.

B. Variable Definitions

The literature shows that basis (B_t) and momentum (M_t),

$$B_t = \frac{F^{T_2}_t}{F^{T_1}_t} - 1 \quad \text{and} \quad M_t = \prod_{s=t-11}^{t} \left(1 + R^{T_1}_{\text{fut},s}\right) - 1, \tag{2}$$

predict nearby futures returns.[7] Szymanowska et al. (2014) find that basis also predicts spreading returns. Miffre (2013) shows that many recently introduced commodity index products take positions conditional on these characteristics. Basis and momentum are thus the most important benchmarks to test whether any new characteristic has marginal predictive content.

We define basis-momentum as the difference between momentum in a first- and second-nearby futures strategy,

$$BM_t = \prod_{s=t-11}^{t} \left(1 + R^{T_1}_{\text{fut},s}\right) - \prod_{s=t-11}^{t} \left(1 + R^{T_2}_{\text{fut},s}\right). \tag{3}$$

Basis-momentum contains important information about the shape of the futures curve, which is determined by the decisions of investors (hedgers, speculators, intermediaries, and, more recently, index investors) to take positions at different horizons. To see why, we use the definitions of first- and second-nearby log futures returns in equations (A4) and (A6) in the Appendix to write basis-momentum as

$$\begin{aligned}\sum_{s=t-11}^{t} r^1_{\text{fut},s} - \sum_{s=t-11}^{t} r^2_{\text{fut},s} &= \sum_{s=t-11}^{t} \left(s_s - f^1_{s-1}\right) - \sum_{s=t-11}^{t} \left(f^1_s - f^2_{s-1}\right) \\ &= \sum_{s=t-11}^{t} b^2_{s-1} - \sum_{s=t-11}^{t} b^1_s,\end{aligned} \tag{4}$$

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 (4) thus decomposes

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

basis-momentum into a measure of average curvature ($\sum_{s=t-11}^{t-1} b_s^2 - \sum_{s=t-11}^{t-1} b_s^1$) and a component that we interpret as a change in slope ($b_{t-12}^2 - b_t^1$). For most observations in our sample, the curve is steeper on the short end, that is, $|b_t^2| < |b_t^1|$. As a result, curvature is positive in backwardation (contango), when first-nearby returns are positive (negative) and higher (lower) than second-nearby returns. Persistence in the steepening or flattening of the slope should similarly predict first-nearby returns in absolute terms and relative to second-nearby returns. Neither basis nor momentum is directly related to curvature.[8]

II. Does Basis-Momentum Predict Returns?

In this section, we examine whether basis-momentum predicts returns in various dimensions. A number of extensions and robustness checks are discussed in Section V.

A. Univariate Sorts

We start by sorting 21 commodities into three portfolios, $p = \{\text{High4, Mid, Low4}\}$, from August 1960 through February 2014. High4 (Low4) includes the four commodities with the highest (lowest) ranked signal; Mid includes all remaining commodities. In each month $t+1$, we calculate equal-weighted nearby and spreading returns of the portfolios ($R_{BM,p,t+1}^{\text{nb}}$ and $R_{BM,p,t+1}^{\text{spr}}$). Recall that expected nearby returns capture spot premiums, and expected spreading returns capture term premiums. As such, these sorts shed light on predictability both in the cross section and across maturity. Our main interest is in the High4-minus-Low4 portfolio. As a benchmark, we sort on basis and momentum.

Panel A in Table I shows high average nearby returns for the High4-minus-Low4 portfolio that are significant across all three sorts. The greatest effect is for basis-momentum, both economically and statistically, at 18.38% ($t = 6.73$) compared to −10.61% ($t = -3.88$) for basis and 15.02% ($t = 4.61$) for momentum. Panel B shows that spreading returns contain a large and significant effect only in the case of basis-momentum at 4.08% ($t = 6.43$). For both nearby returns and spreading returns, the basis-momentum effect is monotonic and translates into a Sharpe ratio of about 0.9.[9]

We conclude that all three signals contain information about nearby returns, but basis-momentum is the strongest of these three predictors. Furthermore, 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

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

[9] In the Internet Appendix, Table IA.II reports similar evidence for the larger set of 32 commodities and Table IA.III finds evidence of high basis-momentum returns in all 10-year subperiods, with less variation across subperiods than for basis and momentum. Consequently, basis-momentum returns cumulate to a relatively large increase in the value of a dollar invested over time, without exposure to extreme drawdowns (see Figure IA.1).

Table I

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: $\prod_{s=t-11}^{t}(1+R_{\text{fut},s}^{T_1}) - \prod_{s=t-11}^{t}(1+R_{\text{fut},s}^{T_2})$) as well as basis ($F_t^{T_2}/F_t^{T_1}-1$) and momentum ($\prod_{s=t-11}^{t}(1+R_{\text{fut},s}^{T_1})$) as a benchmark. The High4 and Low4 portfolios contain the top and bottom four ranked commodities, respectively, whereas the Mid portfolio contains all remaining commodities (the number of which is time-varying). In each postranking month $t+1$, the portfolio's nearby return is the equal-weighted average return of first-nearby contracts ($R_{p,t+1}^{\text{nb}} = R_{p,t+1}^{T_1}$), whereas the spreading return is the equal-weighted average of the difference between the return of the first-nearby and second-nearby contracts ($R_{p,t+1}^{\text{spr}} = R_{p,t+1}^{T_1} - R_{p,t+1}^{T_2}$). We present results for the full sample period from August 1960 through February 2014.

	Basis-Momentum				Basis	Momentum
	High4	Mid	Low4	High4−Low4	High4−Low4	High4−Low4
	Panel A: Nearby Returns ($R_{p,t+1}^{\text{nb}}$)					
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
	Panel B: Spreading Returns ($R_{p,t+1}^{\text{spr}}$)					
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

the fact that these signals are determined by the (average) slope of the futures curve, and not directly by the curvature.

B. Multivariate Tests

We next conduct pooled predictive regressions to show that the basis-momentum effect is robust to controlling for basis and momentum in a joint test:

$$\left\{R_{\text{fut},i,t+1}^{\text{nb}}, R_{\text{fut},i,t+1}^{\text{spr}}\right\} = \lambda_C' C_{i,t} + a_{t+1} + \mu_i + e_{i,t+1}. \tag{5}$$

These regressions also split basis-momentum return predictability into its passive and dynamic components. We start with a model that includes only basis-momentum, $C_{i,t} = BM_{i,t}$, and successively 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 eliminates 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 variation in unconditional average commodity returns, and thus controls for systematic differences across markets. Fama and French (1987) and Moskowitz, Ooi, and Pedersen (2012) find that basis and momentum have predictive power for commodity returns in the time series. Including both fixed effects, $\lambda_{BM,t}$, captures only the dynamic component of basis-momentum return predictability.

Panel A of Table II presents the results for nearby returns.[10] In isolation (column (1)), the coefficient estimate on basis-momentum is positive and significant at 10.45 ($t = 7.45$), which translates into an economically large increase in monthly return of 0.85% for a one-standard-deviation increase in basis-momentum. Consistent with the evidence from our sorts, adding time fixed effects (column (2)) has little effect on the coefficient estimate. More interesting is the similarly large and significant coefficient when we include commodity fixed effects (column (3)), which means that basis-momentum also predicts returns in the time series. When both fixed effects are included (column (4)), the coefficient on lagged basis-momentum remains large and significant at 9.16 ($t = 6.81$), suggesting that the dynamic component of basis-momentum predictability is dominant. Although basis and momentum predict nearby returns in isolation (columns (5) and (6)), the basis-momentum effect is robust to their inclusion (column (7)). In contrast, basis and momentum are insignificant in the joint test.

Panel B shows similarly strong evidence for basis-momentum predictability in spreading returns. In isolation (column (1)), the coefficient estimate on basis-momentum is positive and significant at 2.34 ($t = 6.89$), which translates into an economically large increase in monthly spreading return of 0.20% for a one-standard-deviation increase in basis-momentum. Since the coefficient estimate is only slightly smaller when we control for both time and commodity fixed effects (column (4)), we conclude that spreading return predictability is also driven by the dynamic components of basis-momentum. Basis and momentum do not predict spreading returns.

The last two columns of Panels A and B show similar results when we split the sample in January 1986, so that the second subsample coincides with Szymanowska et al. (2014). Table IA.IV of the Internet Appendix also shows similar evidence for the larger cross section of 32 commodities, even in a specification that includes month $\times$ commodity sector fixed effects.[11] This latter result is interesting as Karstanje, van der Wel, and van Dijk (2015) find strong sector-commonality in the shape of the futures curve. Basis-momentum predictability does not seem to be captured by such commonality.

Panel C of Table II presents the results for two decompositions of basis-momentum. First, we regress returns 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 returns on average curvature and a term related to the change in slope, which, following

[10] Because commodity returns are not strongly autocorrelated, we cluster the standard errors in the time dimension. Results using two-way clustered standard errors are largely identical.

[11] Table IA.I of the Internet Appendix presents the definition and composition of each sector.

Table II

Pooled Regressions of Commodity-Level Returns on Basis-Momentum

This table presents results from pooled regressions of nearby (Panel A) and spreading (Panel B) returns of 21 commodities on lagged characteristics (see equation (5)). Model (1) includes only basis-momentum ($BM_{i,t}$). Models (2) and (3) add time and commodity fixed effects, respectively. Model (4) includes both fixed effects. Models (5) and (6) substitute basis ($B_{i,t}$) or momentum ($M_{i,t}$) 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's. t-statistics are presented underneath each estimate in parentheses and are calculated using standard errors clustered by time. Panel C presents results for two decompositions of basis-momentum over the full sample period. In the left block of results, we regress returns on $M_{i,t}$ and second-nearby momentum ($M_{i,t}^{T_2}$). In the right block of results, we regress returns on curvature and the change in slope (see Section I.B). We present results for the full sample period from August 1960 through February 2014 as well as two sample halves split in January 1986 in the case of Model (7).

	Full Sample							Pre-1986	Post-1986
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(7a)	(7b)
				Panel A: Nearby Returns ($R_{\text{fut},i,t+1}^{\text{nb}}$)					
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)
Time FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Commodity FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.01	0.18	0.01	0.18	0.18	0.18	0.18	0.22	0.16
				Panel B: Spreading Returns ($R_{\text{fut},i,t+1}^{\text{spr}}$)					
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)
Time FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Commodity FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.02	0.03	0.02	0.03	0.03	0.03	0.02	0.04	0.05

Panel C: Decomposing Basis-Momentum Predictability

	$R_{\text{fut},i,t+1}^{\text{nb}}$	$R_{\text{fut},i,t+1}^{\text{spr}}$		$R_{\text{fut},i,t+1}^{\text{nb}}$	$R_{\text{fut},i,t+1}^{\text{spr}}$
λ_M	9.06	1.87	λ_{Curv}	6.08	1.64
(t)	(6.65)	(5.67)		(6.24)	(6.07)
$\lambda_M^{T_2}$	−8.84	−2.23	$\lambda_{\Delta Slope}$	8.71	1.26
(t)	(−5.93)	(−6.50)		(2.95)	(1.61)
Time FE	Yes	Yes		Yes	Yes
Commodity FE	Yes	Yes		Yes	Yes
R^2	0.18	0.04		0.18	0.03

the notation in Section I.B, are defined as

$$Curv_t = \sum_{s=t-11}^{t-1} B_s^{T_2} - \sum_{s=t-11}^{t-1} B_s \tag{6}$$

$$\Delta Slope_t = B_{t-12}^{T_2} - B_t, \tag{7}$$

where B_t is the slope, or basis, defined in equation (2), 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 find that first- and second-nearby momentum significantly predict both nearby and spreading returns, with similar magnitude but opposite sign. The absolute magnitude of these coefficients is similar to the coefficient on basis-momentum in Panels A and B, and we cannot reject the null that the three coefficients are equal at conventional levels of significance. We conclude that the data support the restriction imposed by basis-momentum: the difference in momentum predicts returns. Next, we find that both curvature and change in slope contribute to the excellent performance of basis-momentum. The relative contribution of curvature is greater, however, with an increase in monthly nearby (spreading) return of about 0.60% (0.16%) for a one-standard-deviation increase in $Curv_t$, in comparison with 0.34% (0.05%) for $\Delta Slope_t$.

Overall, the results in this section show that basis-momentum is a powerful predictor of commodity returns that is driven by the dynamic components of spot and term premiums. Basis-momentum predictability is robust to controlling for basis and momentum, but the performance of these benchmark predictors is considerably less impressive when we control for basis-momentum.

III. Is Basis-Momentum a Priced Commodity Factor?

We next analyze whether basis-momentum is a priced 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, which we denote by R_{BM}^{nb} and R_{BM}^{spr}, respectively. Panel A of Table III presents summary statistics for the two basis-momentum factors as well as five benchmark factors. The model of Szymanowska et al. (2014) includes three factors that we construct from a sort on the basis: (i) the nearby return of the High4-minus-Low4 basis portfolio (R_B^{nb}), (ii) the spreading return on the High4 portfolio ($R_{B,\mathrm{High4}}^{\mathrm{spr}}$), and (iii) the spreading return of the Low4 portfolio ($R_{B,\mathrm{Low4}}^{\mathrm{spr}}$). The model of Bakshi, Gao, and Rossi (2017) includes three nearby return factors: (i) an average commodity market factor (i.e., the equal-weighted average return on all commodities, $R_{\mathrm{AVG}}^{\mathrm{nb}}$), (ii) R_B^{nb} as in Szymanowska et al. (2014), and (iii) the High4-minus-Low4 momentum portfolio (R_M^{nb}). This model nests the two-factor model of Yang (2013), which leaves out the momentum factor.

We see that the basis-momentum factors represent attractive investments: average returns are relatively high, while standard deviation, skewness, and kurtosis are similar to the benchmark factors. These higher moments indicate that crash risk is unlikely to explain the basis-momentum effect. The correlations between all factors are below 0.5 in absolute value, indicating substantial independent variation over time.

A. Time-Series Tests

In recent work, Barillas and Shanken (2017, 2018) observe that an unconditional comparison of asset pricing models depends only on the extent to which a model's factors provide an alpha relative to the factors in the other model. Inspired by this observation, Panel B of Table III shows that the two benchmark models do not price the basis-momentum factors. The alpha of R_{BM}^{nb} is high and significant in both models at about 13% ($t > 5$), down from 18% in average returns. Similarly, the alpha of R_{BM}^{spr} is high and significant in both models at about 3.5% ($t > 5$), down from 4% in average returns. The clear rejection with p-values below 10^{-8} in the GRS test (Gibbons, Ross, and Shanken (1989)) underscores that basis-momentum factors provide a high abnormal return and thus improve mean-variance efficiency when added to the benchmark factors.[12]

Table IA.VI of the Internet Appendix examines whether the benchmark factors of Szymanowska et al. (2014) and Bakshi, Gao, and Rossi (2017) are subsumed by models that include the basis-momentum factors. We find that the average and momentum nearby factors provide an alpha relative to a five-factor model including three basis factors and two basis-momentum factors. Next, we analyze the three basis factors relative to two candidate models. The first is a parsimonious model that includes the average and basis-momentum nearby factors. The idea is that these two factors may do a good job capturing the average level of returns and the cross-sectional variation in returns, respectively. The second is a four-factor model that adds the basis-momentum spreading factor (because it provides an abnormal return over the basis factors) and the momentum nearby factor. In short, the pricing information in the basis nearby factor is subsumed by both models. Moreover, only one of the two basis spreading factors (i.e., $R_{B,\mathrm{Low4}}^{\mathrm{spr}}$) provides a significant alpha in each model. Jointly, the alphas for the three basis factors are insignificant at the 1% level in the GRS test. Although it can be shown that a five-factor model that adds $R_{B,\mathrm{Low4}}^{\mathrm{spr}}$ to the four-factor model is mean-variance efficient, given our set of factors, we dismiss this model on economic grounds. It is hard to motivate why the Low4 basis spreading factor contains orthogonal pricing information, whereas the High4 basis spreading factor and the basis nearby factor do not. We, therefore, interpret this evidence as indicating that the four-factor model contains all economically relevant pricing information.

[12] Table IA.V of the Internet Appendix shows that these conclusions are robust to using alternative definitions of the factors. First, we define the factors as the High4-minus-Low4 portfolio from a sort that uses the larger set of 32 commodities. Second, we define the factors as the High-minus-Low portfolio from a sort that splits 21 commodities into two portfolios, based on the median of each characteristic.

Table III

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^{nb}_{BM}) and spreading (R^{spread}_{BM}) return of the High4-minus-Low4 portfolio from univariate sorts of 21 commodities (see Table I). To benchmark these new factors, we also present summary statistics for the factors in two recently developed commodity pricing models. The model of Szymanowska et al. (2014) contains three factors constructed from a sort on the basis ((i) the nearby return for the High4-minus-Low4 basis portfolio (R^{nb}_{B}), (ii) the spreading return of the High4 portfolio ($R^{spr}_{B,\text{High4}}$), and (iii) the spreading return of the Low4 portfolio ($R^{spr}_{B,\text{Low4}}$)); the model of Bakshi, Gao, and Rossi (2017) contains three nearby return factors ((i) an average commodity market factor (R^{nb}_{AVG}), (ii) the nearby basis factor (R^{nb}_{B}), and (iii) the nearby return for the High4-minus-Low4 momentum portfolio (R^{nb}_{M})). Panel B presents results of spanning tests that indicate whether the basis-momentum factors provide an alpha relative to these models. t-statistics are calculated using Newey-West standard errors with lag length one. For the betas: *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Inference from the joint GRS test of these alphas is robust to conditional heteroskedasticity. Results are reported for the full sample period from August 1960 through February 2014.

Panel A: Summary Statistics

						Correlations					
	Avg. Ret.	St. Dev.	Skew.	Kurt.	AR(1)	R^{nb}_{BM}	R^{nb}_{B}	R^{nb}_{AVG}	R^{nb}_{M}	R^{spr}_{BM}	$R^{spr}_{B,\text{High4}}$
R^{nb}_{BM}	18.38	19.99	0.24	5.15	0.09						
R^{nb}_{B}	−10.61	20.01	0.28	6.60	0.04	−0.43					
R^{nb}_{AVG}	5.00	12.96	0.31	7.90	0.03	0.04	−0.06				
R^{nb}_{M}	15.02	23.85	0.07	4.35	0.07	0.27	−0.38	0.10			
R^{spr}_{BM}	4.08	4.65	0.17	5.54	0.05	0.50	−0.26	−0.01	0.17		
$R^{spr}_{B,\text{High4}}$	−1.11	2.50	0.23	5.55	0.11	−0.19	0.36	0.14	−0.15	−0.29	
$R^{spr}_{B,\text{Low4}}$	−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 and GRS Tests

Basis-momentum Factors versus Szymanowska et al. (2014)

	α	(t_α)	β^{nb}_{B}	$\beta^{spr}_{B,\text{High4}}$	$\beta^{spr}_{B,\text{Low4}}$	R^2		
R^{nb}_{BM}	13.82	(5.56)	−0.39***	−0.43	0.19	0.18	GRS-F	23.12
R^{spr}_{BM}	3.49	(6.10)	−0.01	−0.52***	0.32***	0.19	p-val	2.02×10^{-10}

Basis-momentum Factors versus Bakshi, Gao, and Rossi (2017)

	α	(t_α)	β^{nb}_{B}	β^{nb}_{AVG}	β^{nb}_{M}	R^2		
R^{nb}_{BM}	12.76	(5.20)	−0.38***	0.01	0.11**	0.19	GRS-F	19.61
R^{spr}_{BM}	3.32	(5.39)	−0.05***	−0.01	0.02*	0.07	p-val	5.42×10^{-9}

B. Cross-Sectional Tests

We now turn to cross-sectional asset pricing tests to determine whether exposure to a basis-momentum factor is priced and to measure the absolute fit of competing commodity factor pricing models. The latter objective is our primary interest. The reason is that relatively little is known about the cross section of commodities, such that there is a lot of new information in (i) an unconditional test for the broadest cross section of commodity portfolios to date and (ii) a conditional test for individual commodities.

Given previous evidence, we consider six candidate models nested in

$$R_{t+1} = \gamma_{0,t} + \gamma_{1,t}\beta^{\text{nb}}_{BM,t} + \gamma_{2,t}\beta^{\text{nb}}_{B,t} + \gamma_{3,t}\beta^{\text{nb}}_{AVG,t} + \gamma_{4,t}\beta^{\text{nb}}_{M,t} + \gamma_{5,t}\beta^{\text{spr}}_{BM,t} + \gamma_{6,t}\beta^{\text{spr}}_{B,\text{High4},t} + \gamma_{7,t}\beta^{\text{spr}}_{B,\text{Low4},t} + u_{t+1}. \tag{8}$$

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, Gao, and Rossi (2017) (setting $\gamma_{1,t} = \gamma_{5,t} = \gamma_{6,t} = \gamma_{7,t} = 0$). The third and fourth specifications add the basis-momentum nearby factor to these first two models. The fifth specification is the parsimonious 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 final specification is the four-factor model that adds the momentum nearby and basis-momentum spreading factors.

We perform these cross-sectional regressions using both nearby and spreading returns as test assets. This test is motivated by the fact that investors in commodity markets often take positions farther down the futures curve, either because the horizon of their underlying exposure is not matched by the first-nearby contract or because they want to hold a spreading position (perhaps to execute a particular rollover strategy or to hedge out common risk). This approach is similar to Cochrane's (2005) managed portfolios, although we condition on expiration instead of an instrumental variable.

We consider two different cross sections. The first is a set of 16 portfolios sorted on basis, momentum, basis-momentum, and sector.[13] In this portfolio-level test, we estimate full-sample betas, so that β_t is constant over time. Although adding sector portfolios follows the suggestion in Kan, Robotti, and Shanken (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. To address this concern, the second cross section we analyze is the set of 21 individual commodities. This approach follows recent arguments in the literature to run cross-sectional tests for individual stocks rather than portfolios (see, for example, Lewellen, Nagel and Shanken (2010) and Ang, Liu, and Schwarz (2011)). Because betas of individual commodities vary dramatically over time (Bakshi, Gao, and Rossi (2017)), we estimate conditional commodity-level betas over a one-year rolling window of daily returns to keep the betas timely.[14] Daskalaki, Kostakis, and Skiadopoulos (2014) find that the cross section of individual commodities is hard to price, so this exercise presents a challenge for any new factor.

[13] For each characteristic, we use the High4, Mid, and Low4 portfolio from the single sort. The remaining seven sector portfolios are Energy, Meats, Metals, Grains, Oilseeds, Softs, and Industrial Materials. Because there are no Energy and Meats commodities in the first years of our sample, these sectors are included only in the subsample starting in 1986.

[14] We estimate betas only for commodities with over 125 return observations in the window.

Table IV presents annualized risk-price estimates. For the portfolio-level test in Panel A, each estimate is accompanied by two t-statistics, using either Shanken (1992) standard errors (t_S, robust to errors-in-variables in the first-stage betas) and the other estimates or Kan, Robotti, and Shanken (2013) standard errors (t_{KRS}, additionally robust to conditional heteroskedasticity and misspecification). We also present the mean absolute pricing error (*MAPE*) and its decomposition into the part coming from the 16 nearby-portfolio returns and the part due to the 16 spreading-portfolio returns ($MAPE^{\text{nb}}$ and $MAPE^{\text{spr}}$). For the commodity-level test in Panel B, the t-statistics are estimated as in Fama and MacBeth (1973). The R^2 and *MAPE* are from a regression of average commodity returns on average beta to ensure comparability of the cross-sectional fit across panels.

Panel A shows 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%. This estimate is high compared to the average return of this factor: −10.61%. The estimated prices of risk for the two basis spreading return factors are economically and statistically lower. The fit improves for the three-factor model of Bakshi, Gao, and Rossi (2017), with an R^2 of 0.80 and a *MAPE* of 1.53%, and all three factor risk prices are significant. The third and fourth specifications show that the basis-momentum nearby factor is significantly priced when added to each of these benchmark models, at about 18% ($t_{KRS} > 3.5$), which translates into a Sharpe ratio of about 0.85. This estimate is close to the factor's average return, and thus satisfies this important reality check (see Lewellen, Nagel, and Shanken (2010)). Adding basis-momentum improves the cross-sectional fit substantially to R^2s (*MAPE*s) of 0.79 and 0.92 (1.76% and 1.05%), respectively.

In the fifth specification, we see that the fit of the parsimonious two-factor model, including the average and basis-momentum nearby factors, is comparable to that of the three- and four-factor models, with an R^2 of 0.85 and *MAPE* of 1.38%. Consistent with the evidence from the last subsection, the four-factor model in the last specification gives a slightly better cross-sectional fit ($R^2 = 0.92$ and $MAPE = 1.00\%$). There is a sign of overfitting, as the estimated risk prices for the two correlated basis-momentum factors are marginally insignificant using Kan, Robotti, and Shanken (2013) standard errors.

The pricing evidence for basis-momentum is robust in the conditional commodity-level test of Panel B. First, exposure to the basis-momentum nearby factor captures a high and significant price of risk of about 15% (or 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 is again similar to that of the 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. The intuition behind the result for momentum is that a commodity with high past 12-month returns will not necessarily have a large positive exposure to the momentum factor when this exposure is estimated over a backward-looking rolling window. In this light, the robust pricing of the basis-momentum factor in this conditional test is important for its

Table IV

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_B^{nb}) as well as the spreading return of both the High4 and the Low4 basis portfolios ($R_{B,\mathrm{High4}}^{\mathrm{spr}}$ and $R_{B,\mathrm{Low4}}^{\mathrm{spr}}$). The second model of Bakshi, Gao, and Rossi (2017) contains three nearby factors: a market index ("the average factor," $R_{\mathrm{AVG}}^{\mathrm{nb}}$), a basis factor ($R_B^{\mathrm{nb}}$), and a momentum factor (R_M^{nb}). The third and fourth models add the basis-momentum nearby factor (R_{BM}^{nb}) 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 momentum nearby and basis-momentum spreading factors to this specification (R_M^{nb} and R_{BM}^{spr}). 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 returns of nine portfolios sorted on basis-momentum, basis, and momentum (the High4, Mid, and Low4 portfolios from each of these sorts) and seven 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 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 parentheses) and Kan, Robotti, and Shanken (2013) (in angle brackets) in Panel A and Fama and MacBeth (1973) (in parentheses) in Panel B. Also, we present the cross-sectional R^2 and the mean absolute pricing error (*MAPE*, in brackets), which is further decomposed into 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 through February 2014, but we also summarize the evidence for two subsamples (split in January 1986 and focusing on the price of risk for the nearby basis-momentum factor and the cross-sectional fit).

	Full Sample										Pre-1986		Post-1986	
	γ_0	$\gamma_{BM}^{\mathrm{nb}}$	γ_B^{nb}	$\gamma_{\mathrm{AVG}}^{\mathrm{nb}}$	γ_M^{nb}	$\gamma_{BM}^{\mathrm{spr}}$	$\gamma_{B,\mathrm{High4}}^{\mathrm{spr}}$	$\gamma_{B,\mathrm{Low4}}^{\mathrm{spr}}$	R^2 *MAPE*	*MAPE*$^{\mathrm{nb}}$ *MAPE*$^{\mathrm{spr}}$	$\gamma_{BM}^{\mathrm{nb}}$	R^2	$\gamma_{BM}^{\mathrm{nb}}$ *MAPE*	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]
	<0.46>		<−4.12>				<1.71>	<−2.01>						
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]
	<−2.98>		<−3.54>	<2.21>	<2.45>									

(*Continued*)

Table IV—*Continued*

	Full Sample										Pre-1986		Post-1986	
	γ_0	γ_{BM}^{nb}	γ_B^{nb}	γ_{AVG}^{nb}	γ_M^{nb}	γ_{BM}^{spr}	$\gamma_{B,High4}^{spr}$	$\gamma_{B,Low4}^{spr}$	R^2 *MAPE*	$MAPE^{nb}$ $MAPE^{spr}$	γ_{BM}^{nb}	R^2	γ_{BM}^{nb} *MAPE*	R^2 *MAPE*
Panel A: Portfolio-Level Test with Full Sample Betas														
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]
	<0.281>	<3.54>	<−2.77>				<1.79>	<−2.01>			<2.08>		<2.58>	
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]
	<−3.32>	<3.68>	<−0.92>	<2.14>	<2.16>						<2.83>		<2.08>	
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]
	<−3.56>	<6.26>		<2.43>							<5.53>		<3.79>	
Model 6	−0.95	18.35		5.35	15.39	4.56			0.92	[1.26]	21.59	0.91	17.28	0.80
	(−3.40)	(5.98)		(2.94)	(4.53)	(3.24)			[1.00]	[0.74]	(5.01)	[1.29]	(3.93)	[1.61]
	<−3.33>	<1.42>		<2.23>	<2.36>	<1.41>					<1.75>		<1.60>	
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	0.15	17.80		4.23	3.71	2.40			0.83	[2.08]	12.90	0.54	22.36	0.81
	(0.40)	(4.54)		(2.35)	(0.85)	(1.80)			[1.33]	[0.58]	(2.40)	[2.38]	(3.96)	[1.50]

interpretation as a true risk factor. Finally, the estimated intercept is economically small in all specifications, although it is significant in some portfolio-level tests at about −1%.

Given these results and consistent evidence from a range of robustness checks, we draw two conclusions.[15] First, exposure to the basis-momentum nearby factor is priced, and contains independent information about the cross section of average commodity returns, which is consistent with the factor's alpha (see Table III). Second, a parsimonious two-factor model combining basis-momentum with an average commodity market factor provides excellent cross-sectional fit. Figure IA.2 in the Internet Appendix presents scatter plots of average returns versus model-predicted returns and confirms that average nearby and spreading returns line up relatively well in the two-factor model.

Larger four-factor models (particularly the fourth and sixth specifications) provide slightly better cross-sectional fit, but the pricing performance of the additional factors is sensitive to the specification of the asset pricing test. The basis nearby factor does not provide an alpha beyond that of the two-factor model and is insignificant using Kan, Robotti, and Shanken (2013) standard errors in specification four of the portfolio-level test. However, in the conditional commodity-level test, the basis nearby factor is significant. In contrast, the momentum nearby factor does provide an alpha, but it is not robustly priced in the conditional test. Finally, although the basis-momentum spreading factor provides an alpha over the benchmark factors, it does not add much pricing information when a basis-momentum nearby factor is already included in the cross-sectional test.

IV. Testing Potential Explanations for Basis-Momentum

Having established the asset pricing implications of basis-momentum, we consider the economic determinants of the documented effects. We start by examining classical commodity pricing theories that rely on storage and the position of hedgers. Next, we analyze implications from asset pricing theories that ascribe a key role to speculators and financial intermediaries.

A. Storage and Inventory

Gorton, Hayashi, and Rouwenhorst (2012, henceforth GHR) link commodity futures risk premiums to the level of physical inventories. This link follows from a simple model that integrates the theory of storage (Kaldor (1939), Working (1949), and Deaton and Laroque (1992)) and the theory of normal backwardation of Keynes (1930). In the model of GHR, when initial inventory levels are high enough to allow inventory holders to move the commodity from the

[15] Our results are similar when we (i) divide the sample into two (see the last four columns of Panels A and B), (ii) perform the tests for the larger set of 32 commodities (see Panels A and B of Table IA.VII in the Internet Appendix), and (iii) use the High-minus-Low factors that are split at the median (see Panel C of Table IA.VII).

present to the future, the convenience yield is zero and the futures price is above the spot price as determined by the cost of storage. Otherwise, in the event of a stock-out, the convenience yield is positive, reflecting a spot price increase due to a shortage of goods, and the futures price may fall below the spot price. The convenience yield is therefore a declining and convex function of inventories. Under the realistic condition that the volatility of future spot prices falls fast enough with an increase in inventories, the futures risk premium will decline with inventories. Further testable implications are that low-inventory commodities have a low basis (defined as the futures price over the spot price), high prior returns, and high volatility. GHR note that these price-based measures of inventory risk are attractive empirically because publicly reported inventory data provide only a noisy measure of the true state of inventories. We analyze the relation between basis-momentum and these various measures using double sorts. We also test whether there is a basis-momentum effect in currencies, stock indexes, and bond indexes. If the dynamics of storage and inventory drive basis-momentum in commodity markets, we should not find a basis-momentum effect in financial assets that can be stored costlessly.

A.1. Double Sorts: Basis-Momentum versus Inventory-Related Variables

Table V presents the results from independent double sorts of the cross section of 21 commodities into two basis-momentum groups and two control groups. The first three controls are basis, momentum, and volatility. Following GHR, volatility is demeaned at the commodity level and is forward-looking (i.e., calculated ex post using daily returns in month $t + 1$). Next, we form two control groups on normalized inventory, defined as current inventory over last year's average inventory.[16] Finally, we control for storability, where we split the sample into "more" and "less" storable commodities. This last test is motivated by the idea that inventory dynamics are more relevant for commodities that are difficult to store.[17]

Panel A shows that a single sort on basis, momentum, volatility, and normalized inventory provides a large and significant High-Low spread in nearby returns of −9.31%, 8.01%, 7.86%, and −6.95%, respectively. The signs of these effects are consistent with the model of GHR. Storability does not predict returns. The last two columns show that the High-minus-Low basis-momentum effect in nearby returns is large and significant in all control groups (above 12.70%). Panel B shows that normalized inventory is the only control variable that is significantly related to spreading returns. Again, the basis-momentum effect in spreading returns is robust in all control groups (above 1.98%), and we observe a large difference in spreading return only between the High-Low

[16] We thank Geert Rouwenhorst for sharing the inventory data with us.

[17] From Table 3 of GHR, the 15 (of 32) "more storable" commodities are Soybeans, Soybean meal, Cocoa, Cotton, Feeder Cattle, Oats, Coffee, Corn, Palladium, Lumber, Rubber, Copper, Platinum, Gold, and Silver.

Table V

Double Sorts: Basis-Momentum versus Inventory-Related 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). The 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), momentum (split at the median), volatility (measured ex post as the volatility of daily returns in month $t+1$ and split at the median), normalized inventory (defined as inventory in month t as a fraction of last year's average inventory and split at the median), storability (where the sample is split into 17 "less" storable commodities and 15 "more" storable commodities), and, the 12-month average basis (split at zero). 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 postranking 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 contracts. We present results for the full sample period (using only those months where we have at least eight commodities with available data) with one exception: the sample for inventory runs from 1970 through 2010 as in Gorton, Hayashi, and Rouwenhorst (2012).

		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 A: Nearby Returns ($R^{\mathrm{nb}}_{p,t+1}$)									
Basis-momentum	High	14.01	(5.32)						
	Low	−3.13	(−1.35)						
	Diff	17.14	(7.60)						
Basis	Contango	1.48	(0.66)	10.98	(3.90)	−3.94	(−1.65)	14.92	(5.83)
	Backwardation	10.80	(3.72)	14.68	(4.21)	−0.11	(−0.04)	14.79	(3.90)
	Diff	−9.31	(−3.74)	−3.70	(−1.10)	−3.83	(−1.33)		
Momentum	Winners	9.21	(3.47)	15.20	(5.13)	−0.03	(−0.01)	15.23	(4.63)
	Losers	1.20	(0.52)	11.92	(3.66)	−4.37	(−1.76)	16.29	(5.17)
	Diff	8.01	(3.49)	3.28	(1.04)	4.34	(1.35)		
Volatility	High	9.10	(2.85)	18.02	(4.76)	−0.16	(−0.05)	18.19	(4.87)
	Low	1.25	(0.70)	10.30	(4.48)	−6.96	(−3.85)	17.26	(8.05)
	Diff	7.86	(3.02)	7.72	(2.19)	6.79	(2.18)		

(*Continued*)

Table V—*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 A: Nearby Returns ($R^{\mathrm{nb}}_{p,t+1}$)									
Inventory	High	2.04	(0.81)	9.36	(3.01)	−3.34	(−1.14)	12.70	(3.97)
	Low	8.98	(3.52)	15.94	(5.30)	0.13	(0.04)	15.81	(5.28)
	Diff	−6.95	(−3.23)	−6.58	(−2.06)	−3.47	(−1.24)		
Storage	More storable	6.45	(2.67)	15.49	(4.59)	−1.40	(−0.51)	16.89	(4.84)
	Less storable	3.99	(1.62)	13.24	(4.40)	−4.28	(−1.56)	17.52	(6.07)
	Diff	2.45	(1.12)	2.24	(0.65)	2.87	(1.02)		
Panel B: Spreading Returns ($R^{\mathrm{spr}}_{p,t+1}$)									
Basis-momentum	High	0.96	(2.63)						
	Low	−2.08	(−7.10)						
	Diff	3.04	(7.07)						
Basis	Contango	−0.61	(−2.99)	0.50	(1.67)	−1.48	(−5.50)	1.98	(5.22)
	Backwardation	−0.74	(−1.35)	0.39	(0.58)	−3.36	(−4.68)	3.75	(4.16)
	Diff	0.14	(0.24)	0.11	(0.16)	1.88	(2.59)		
Momentum	Winners	−0.42	(−1.01)	0.94	(1.72)	−2.28	(−4.21)	3.21	(4.80)
	Losers	−0.82	(−3.08)	1.02	(2.02)	−1.87	(−5.79)	2.89	(5.02)
	Diff	0.40	(0.83)	−0.09	(−0.12)	−0.41	(−0.70)		
Volatility	High	−0.26	(−0.58)	0.57	(0.69)	−1.73	(−3.47)	2.31	(2.66)
	Low	−0.96	(−4.01)	0.67	(1.70)	−2.34	(−7.57)	3.00	(6.31)
	Diff	0.70	(1.40)	−0.09	(−0.10)	0.60	(1.10)		
Inventory	High	−1.33	(−4.50)	0.15	(0.28)	−2.45	(−5.82)	2.60	(3.58)
	Low	0.41	(1.14)	1.85	(3.32)	−1.38	(−3.27)	3.23	(4.75)
	Diff	−1.74	(−4.18)	−1.70	(−2.19)	−1.07	(−1.85)		
Storage	More storable	−0.36	(−0.99)	1.64	(3.06)	−1.96	(−4.30)	3.60	(5.32)
	Less storable	−0.81	(−2.55)	0.45	(0.96)	−2.12	(−5.75)	2.58	(4.86)
	Diff	0.45	(0.96)	1.18	(1.74)	0.16	(0.29)		

basis-momentum portfolio among commodities in backwardation (3.75%) versus contango (1.98%).

Overall, we conclude that basis-momentum predictability is not captured by and does not interact strongly with measures of inventory risk. Table V shows that the High-Low spreads for these measures are considerably more narrow when we separate the sample in High and Low basis-momentum commodities. These findings underscore the previous conclusion that basis-momentum is a relatively strong predictor that contains orthogonal information about commodity returns.

A.2. Basis-Momentum in Alternative Asset Classes

We next test whether there is a basis-momentum effect in three alternative asset classes. Section I of the Internet Appendix presents a detailed description of the data and method. Our currency sample covers 48 currencies from December 1996 through August 2015. For each currency, we use spot and one- and two-month forward exchange rates to define the nearby return, $R^1_{\mathrm{cur},t+1} = S_{t+1}/F^1_t - 1$, and spreading return, $R^1_{\mathrm{cur},t+1} - (F^1_{t+1}/F^2_t - 1)$. The sample of stock indexes includes 12 markets for which we collect first- and second-nearby futures prices, and we calculate returns analogous to commodity futures. Dictated by data availability, the stock index sample runs from August 2001 through December 2014. The sample of bond indexes includes 10 markets. As in Koijen et al. (2018), we calculate synthetic returns for one- and six-month futures contracts on a 10-year zero-coupon bond using the yield curve data of Wright (2011). The sample period is February 1991 through May 2009. We report only nearby returns for these bond indexes. In contrast to spreading returns, synthetic nearby returns are highly correlated with actual bond futures returns. As before, we sort assets in each market into a High4 and Low4 portfolio using basis-momentum, basis, and momentum.

Table VI presents the results for currencies in Panel A. Currency returns increase monotonically with basis-momentum. The nearby and spreading returns of the High4-minus-Low4 portfolio are high and significant at 8.06% ($t = 3.47$) and 0.78% ($t = 2.32$), respectively. The nearby return translates into a Sharpe ratio of 0.81, which is only slightly below a value of 0.92 for commodities (see Table I). The Sharpe ratio of the spreading return is considerably lower than that for commodities, at 0.54 compared to 0.88. Moreover, this spreading return is present only in emerging currencies. In contrast, the basis-momentum effect in nearby returns is present in both developed and emerging currencies.

Panel B shows that stock index returns also increase monotonically with basis-momentum. Both nearby and spreading returns for the High4-minus-Low4 portfolio are marginally significant at 3.65% ($t = 1.80$) and 1.03% ($t = 1.88$), respectively. These returns translate into Sharpe ratios slightly over 0.50, which is high economically but lower than for commodities. Panel C shows similar evidence for bond indexes at an average nearby return of 2.69% ($t = 2.23$) and a Sharpe ratio of 0.52. Because our focus is on commodity markets, we leave a thorough investigation of basis-momentum in

Table VI

Double Sorts: Basis-Momentum in Alternative Asset Classes

This table presents unconditional performance measures for equal-weighted currency (Panel A), stock index (Panel B), and bond index (Panel C) portfolios sorted on basis-momentum, basis, and momentum. Section I of the Internet Appendix contains a description of the sample of 48 currencies (equally split between 24 developed and 24 emerging markets), 12 stock indexes, and 10 bond indexes. The nearby currency forward return is the return from buying a currency at the one-month forward price. The spreading currency forward return subtracts from this nearby return the return from closing a two-month currency forward contract one month after initiation. Nearby and spreading returns for the stock index futures are defined analogously to those for commodities. Nearby returns for the bond indexes are synthetic and derived from the zero coupon yield curve. We do not report spreading returns for bond indexes, as these cannot be closely matched to actual bond futures returns. The High4 and Low4 portfolios contain the top and bottom assets in each cross section, respectively. We require eight assets with available data to perform our sorts. Hence, the currency sample runs from April 1997 through August 2015, the stock index sample from August 2002 through December 2014, and the bond index sample from February 1991 through May 2009.

	Basis-Momentum				Basis	Momentum
	High4	Mid	Low4	High4−Low4	High4−Low4	High4−Low4
Panel A: Currencies						
Nearby Returns ($R^1_{\text{cur},p,t+1}$)						
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
Sharpe(Developed)	0.26	0.16	−0.16	0.69	−0.95	0.11
Sharpe(Emerging)	0.62	0.24	−0.04	0.64	−0.61	0.64
Spreading Returns ($R^1_{\text{cur},p,t+1} - R^2_{\text{cur},p,t+1}$)						
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
Sharpe(Developed)	0.20	0.12	0.13	0.05	−0.56	0.06
Sharpe(Emerging)	0.54	0.53	−0.41	0.68	−0.23	−0.04
Panel B: Stock Indexes						
Nearby Returns ($R^{T_1}_{\text{stock},p,t+1}$)						
Avg. ret.	6.82	5.76	3.17	3.65	−1.79	0.27
(t)	(1.53)	(1.27)	(0.73)	(1.80)	(−0.86)	(0.12)
Sharpe	0.44	0.37	0.21	0.52	−0.25	0.03
Spreading Returns ($R^{T_1}_{\text{stock},p,t+1} - R^{T_2}_{\text{stock},p,t+1}$)						
Avg. ret.	0.91	0.13	−0.12	1.03	1.14	−0.21
(t)	(1.94)	(0.50)	(−0.36)	(1.88)	(1.95)	(−0.40)
Sharpe	0.56	0.15	−0.10	0.54	0.56	−0.11

(Continued)

Table VI—*Continued*

	Basis-Momentum				Basis	Momentum
	High4	Mid	Low4	High4-Low4	High4-Low4	High4-Low4
Panel C: Bond Indexes						
Nearby Returns ($R^1_{\text{bond},p,t+1}$)						
Avg. ret.	6.13	5.98	3.44	2.69	−3.46	−2.32
(t)	(3.63)	(3.45)	(2.24)	(2.23)	(−2.79)	(−1.85)
Sharpe	0.85	0.81	0.52	0.52	−0.65	−0.43

these alternative asset classes to future work. Nonetheless, because the underlying financial assets can be stored costlessly and a basis-momentum effect is present, these results again suggest that storage is unlikely to explain much of the returns to basis-momentum.

B. Hedging Pressure and Positions of Traders

We next analyze the relation between basis-momentum and the position of traders. Because the Commitment of Traders reports from the Commodity Futures Trading Commission (CFTC) are aggregated at the commodity level, we follow the literature and define hedging pressure as the difference between the number of short and long positions of commercials as a fraction of open interest. Using the same data, we define (speculator) spreading pressure as the number of noncommercial spreading positions as a fraction of open interest. Spreading positions measure the extent to which an individual noncommercial trader holds equal long and short futures positions in a commodity, independent of the delivery month. To the best of our knowledge, an analysis of spreading positions is new in the literature. Data availability restricts our analysis to a shorter time series from 1986 onward.

Following Kang, Rouwenhorst, and Tang (2016), we use a backward-looking 12-month average of hedging pressure (denoted *HP*). The economic motivation is that this component of hedger-reported positions better captures true hedging demands, which are not well captured by the high-frequency fluctuations in observed monthly hedging pressure.[18] Empirically, we find that 12-month average hedging pressure is a relatively strong predictor of returns.[19] Thus, we give this theory a better chance to capture part of the basis-momentum effect. Similarly, we take a three-month average of spreading pressure (denoted *SP*), as we find that this component of spreading pressure is most strongly related to future returns.

[18] Kang, Rouwenhorst, and Tang (2016) argue that these high-frequency fluctuations in hedging pressure capture liquidity provision from hedgers to speculators who follow momentum strategies.

[19] Szymanowska et al. (2014) and Gorton, Hayashi, and Rouwenhorst (2012) find that monthly hedging pressure does not predict returns. A possible alternative explanation, which we do not analyze, relates to shortcomings in the hedger classification by the CFTC (see, for example, Acharya, Lochstoer, and Ramadorai (2013), and Dewally, Ederington, and Fernando (2013)).

Table VII

Pooled Regressions: Basis-Momentum versus Positions of Traders

This table analyzes how basis-momentum interacts with hedging and spreading pressure, respectively, defined as the total number of short minus long positions of commercials (hedgers) and the total number of spreading positions of noncommercials (speculators) as a fraction of open interest. For this analysis, we take a 12-month average of hedging pressure (*HP*) and a three-month average of spreading pressure (*SP*). Panel A presents the correlation between these measures and basis-momentum as well as basis (*B*) and momentum (*M*). The time-series correlation is calculated as the median over 21 commodities of the correlation between a position measure and a characteristic. The cross-sectional correlation is calculated as the median over time of the correlation between a position measure and a characteristic. Panel B presents results from pooled regressions for both nearby and spreading returns. For this regression, *HP* and *SP* are converted into dummy variables indicating whether a position measure is above the median for a given commodity (I_{HP} and I_{SP}). Model (1) includes only basis-momentum (*BM*) as an independent variable. Model (2) adds the position dummies. Model (3) adds the interaction effects. All regressions include time fixed effects. The t-statistics presented underneath each estimate are calculated using standard errors clustered in the time dimension. The sample period is from February 1986 through February 2014, dictated by availability of CFTC position data.

Panel A: Correlation Position Measures and Characteristics

	Time-Series Correlation			Cross-Sectional Correlation		
	BM	*B*	*M*	*BM*	*B*	*M*
HP	−0.04	−0.22	0.46	0.14	−0.11	0.27
SP	−0.25	0.15	0.00	−0.04	−0.01	0.00

Panel B: Pooled Regressions

	Nearby Returns ($R^{\text{nb}}_{\text{fut},i,t+1}$)			Spreading Returns ($R^{\text{spr}}_{\text{fut},i,t+1}$)		
Model	(1)	(2)	(3)	(1)	(2)	(3)
BM	8.67	8.49	5.39	2.38	2.37	−0.19
(t)	(4.59)	(4.49)	(1.74)	(4.09)	(4.10)	(−0.20)
I_{HP}		0.42	0.39		−0.03	−0.04
(t)		(1.97)	(1.78)		(−0.74)	(−0.90)
I_{SP}		−0.50	−0.44		−0.10	−0.05
(t)		(−2.13)	(−1.81)		(−2.16)	(−1.11)
$BM \times I_{HP}$			−0.45			0.24
(t)			(−0.14)			(0.27)
$BM \times I_{SP}$			6.19			4.44
(t)			(1.75)			(4.10)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.17	0.17	0.17	0.03	0.03	0.05

In Panel A of Table VII, we present the time series (averaged over commodities) and cross-sectional (averaged over time) correlation between these position measures and characteristics. Consistent with the results in Kang, Rouwenhorst, and Tang (2016), momentum is relatively strongly correlated with *HP* in both the time series and the cross section. Basis-momentum is relatively strongly negatively correlated with *SP* in the time series, suggesting that for the average commodity basis-momentum increases when speculators are reducing their spreading positions. We also see a moderate positive cross-sectional correlation between basis-momentum and *HP*. We conclude that it is important to control for *HP* and *SP* in both the time series and the cross section when analyzing basis-momentum return predictability.

To do so, we run a pooled regression (with time fixed effects),

$$\left\{R^{\mathrm{nb}}_{\mathrm{fut},i,t+1}, R^{\mathrm{spr}}_{\mathrm{fut},i,t+1}\right\} = a_{t+1} + \lambda_{BM} BM_{i,t} + \lambda_2 I_{HP,i,t} + \lambda_3 I_{SP,i,t} + \lambda_4 I_{HP,i,t} \times BM_{i,t} + \lambda_5 I_{SP,i,t} \times BM_{i,t} + e_{i,t+1}, \qquad (9)$$

where $I_{HP,i,t}$ and $I_{SP,i,t}$ are dummies that are equal to one when a position measure is above the time-series median for commodity i in month t. This dummy specification is attractive as it controls for differences in the average of *HP* and *SP* across commodities, is less affected by CFTC classification issues, and accommodates interpretation of the interaction effects.

Panel B of Table VII presents the results. First, we find that the coefficient on basis-momentum is virtually unaffected by the inclusion of the position measures at 8.49%, relative to the case without controls at 8.67%. We further find that *HP* does predict nearby returns with a positive sign, consistent with the theory of hedging pressure, while *SP* predicts both nearby and spreading returns with a negative sign. The fact that spreading pressure predicts returns has not been documented in the literature before. In the specification with interaction effects, we see that basis-momentum predictability interacts significantly with spreading pressure, but not with hedging pressure. For nearby returns, the coefficient on $BM_{i,t}$ falls to 5.39%, while the coefficient on $I_{SP,i,t} \times BM_{i,t}$ is large at 6.19%. Taken together, these numbers imply that the basis-momentum effect more than doubles when *SP* is above the median for a commodity. For spreading returns, the coefficient on $BM_{i,t}$ is virtually zero, while the coefficient on $I_{SP,i,t} \times BM_{i,t}$ equals 4.44%. These numbers imply that basis-momentum predicts spreading returns only when *SP* is relatively high.[20]

Overall, the evidence suggests that speculators' decision to establish spreading positions contains important information about returns and basis-momentum predictability. This evidence highlights the economic interest in analyzing position data at the commodity-maturity level, data that are currently not publicly available from the CFTC. Indeed, knowing whether speculators are going long nearby contracts and short farther-from-expiring contracts, or vice versa, is crucial to test potential explanations of the spreading pressure effect we document. Also, the evidence suggests a role for volatility and liquidity in explaining basis-momentum. Spreading positions are attractive to ensure continuous exposure at lower transaction costs and execution risk.[21] Furthermore, speculators, and financial intermediaries more generally, might be averse to taking directional exposure to a commodity in times of high uncertainty and

[20] Table IA.IX of the Internet Appendix presents double sorts that support the same conclusions.

[21] Most index providers require tradable spreading positions for a commodity to be included in an index.

thus opt for a spreading position. This idea is implicit in classical inventory models such as Stoll (1978), in which dealers hedge suboptimal inventory positions, especially when volatility is high. In addition, Kang, Rouwenhorst, and Tang (2016) argue that speculator trades often take liquidity, which in the case of spreading positions would imply a differential price impact across the curve. To address these suggestions about the role of speculators, we turn to the relation between basis-momentum, volatility, and liquidity in the following subsection.

C. Volatility

We test whether basis-momentum is related to volatility in two dimensions. First, we ask whether volatility predicts basis-momentum returns in the time series. The motivation is that basis-momentum could capture returns to liquidity provision when there are imbalances in the supply and demand of futures contracts within and across commodity futures curves. Brunnermeier and Pedersen (2009), Brunnermeier, Nagel, and Pedersen (2008), and Nagel (2012) argue that these returns should increase with volatility. Second, we test whether covariance with volatility shocks is priced in the cross section, and whether volatility risk is driven out by exposure to the basis-momentum factor. The cross-sectional approach allows us to pin down the asset pricing implications of volatility risk, and a negative price of volatility risk would mean that investors are willing to pay for insurance against increases in volatility.

We consider both aggregate and average commodity volatility to ensure that the volatility factor is economically relevant for diversified commodity investors, such as speculators and financial intermediaries. The double sorts in Table V show that the basis-momentum effect is about the same in commodity months with high and low volatility. Thus, a story based on commodity-specific volatility, which is more relevant for hedgers that trade in one or a few commodities, cannot explain basis-momentum. We compute aggregate commodity market variance in month t, $\text{var}_t^{\text{mkt}}$, as the sum of squared daily returns on an equal-weighted commodity index, which is similar to the measure of Guo (2006) for the aggregate stock market. We compute average commodity market variance in month t, $\text{var}_t^{\text{avg}}$, as the equal-weighted average of the sum of squared daily returns of individual commodities.

C.1. Volatility and the Time Series of Basis-Momentum Returns

We regress basis-momentum portfolio returns on lagged variance,

$$\left\{R_{p,t+1:t+k}^{\text{nb}}, R_{p,t+1:t+k}^{\text{spr}}\right\} = v_0 + v_1 \text{var}_t + e_{t+1:t+k}, \qquad (10)$$

where the left-hand-side returns are compounded over $k = \{1, 6, 12\}$ months, and the right-hand-side predictor is standardized to accommodate interpretation. Panel A of Table VIII presents the estimated coefficient v_1, its t-statistic computed using Newey-West standard errors with k lags, and the regression

Table VIII

Does Volatility Predict Basis-Momentum Returns?

This table analyzes whether basis-momentum returns are increasing in lagged volatility. Aggregate commodity market variance, $\text{var}_t^{\text{mkt}}$, is calculated as the sum of squared daily returns on an equal-weighted commodity index, and average commodity market variance, $\text{var}_t^{\text{avg}}$, is calculated as the equal weighted average of the sum of squared daily returns of individual commodities. Panel A presents coefficient estimates, υ_1, from time-series regressions of basis-momentum portfolio returns (compounded over horizons of $k = 1, 6, 12$ months) on lagged variance, which is standardized to accommodate interpretation (see equation (10)). The regression is estimated using WLS, weighting each nearby ($R^{\text{nb}}_{p,t+1:t+k}$) and spreading ($R^{\text{spr}}_{p,t+1:t+k}$) return observation by the inverse of conditional volatility. We use the standard deviation of returns from $t-11$ to t as a simple proxy for conditional volatility in month $t+1$. 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 a burn-in period for the estimation of the medians. Standard errors are Newey-West with lag length k (1) in Panel A (B). The sample period is August 1960 through February 2014.

Panel A: Predicting Basis-Momentum Returns with Lagged Volatility

	Basis-Momentum						Basis	Momentum
k	1 High4	Mid	Low4	H4-L4	6 H4-L4	12 H4-L4	12 H4-L4	12 H4-L4
	Nearby Returns ($R^{\text{nb}}_{p,t+1:t+k}$)							
υ_1^{mkt}	5.96	−0.75	−0.30	9.31	8.64	7.09	−3.33	−2.51
(t)	(1.32)	(−0.22)	(−0.08)	(2.45)	(2.89)	(2.17)	(−1.21)	(−0.89)
R^2	0.01	0.02	0.00	0.03	0.09	0.10	0.06	−0.02
υ_1^{avg}	4.61	−6.46	−0.84	9.09	7.35	6.45	−1.00	−0.32
(t)	(1.15)	(−1.50)	(−0.26)	(2.90)	(2.92)	(2.23)	(−0.34)	(−0.09)
R^2	0.01	0.03	0.00	0.03	0.09	0.10	0.05	−0.03
	Spreading Returns ($R^{\text{spr}}_{p,t+1:t+k}$)							
υ_1^{mkt}	−0.20	−0.17	−1.40	1.16	1.35	1.24	0.25	−0.02
(t)	(−0.92)	(−0.64)	(−2.83)	(1.55)	(2.74)	(3.75)	(0.28)	(−0.04)
R^2	0.01	0.03	0.00	0.03	0.12	0.14	0.08	0.00
υ_1^{avg}	−0.26	−0.12	−1.79	1.42	1.45	1.39	0.82	−0.09
(t)	(−0.92)	(−0.41)	(−3.75)	(1.93)	(3.02)	(3.75)	(0.84)	(−0.14)
R^2	0.01	0.03	0.02	0.03	0.13	0.16	0.10	0.00

Panel B: Basis-Momentum in High Volatility versus Normal Months

	H4-L4 Nearby Returns			H4-L4 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

R^2. Coefficients are estimated using weighted least squares, downweighting the most volatile ex post return observations to increase efficiency.[22]

The first three rows show that aggregate commodity market variance predicts nearby returns significantly at all horizons. The effect is economically large: a one-standard-deviation increase in variance is associated with an increase in annualized nearby return of the High4-minus-Low4 portfolio of 9.31% for $k = 1$ and 7.09% for $k = 12$. For spreading returns, the effects are also large, with an increase in spreading return of 1.16% for $k = 1$ and 1.24% for $k = 12$. The results are similar for our measure of average commodity market variance. In contrast, we find that returns on basis and momentum strategies are not predictable by lagged volatility. Panel B presents results for an out-of-sample exercise that conditions basis-momentum returns on lagged volatility (relative to its historical median), separating the sample into high volatility months and normal months. We find that High4-minus-Low4 returns are about twice as high after high-volatility months, and the difference is significant for both nearby and spreading returns.

We conclude that commodity market volatility predicts returns on basis-momentum strategies with a positive sign, which is consistent with explanations based on time-varying returns to liquidity provision. The correlation between these volatility measures and aggregate spreading positions is about 0.5, consistent with the idea that speculators and financial intermediaries dislike directional exposure to commodities in times of high volatility.

C.2. Volatility Risk in the Cross Section

Table IX presents results of asset pricing tests for volatility risk using the cross section of nearby and spreading returns of 16 commodity-sorted portfolios. We analyze two-factor models that include the average commodity market factor and one of the volatility risk factors as well as three-factor models that control for the basis-momentum factor. We define the aggregate and average volatility risk factor as the first-difference in the corresponding series: $\Delta\text{var}^{\text{mkt}}_{t+1}$ and $\Delta\text{var}^{\text{avg}}_{t+1}$.

We find that exposure to volatility risk captures a large and significant negative price of risk. The point estimates translate into a Sharpe ratio of about -0.65 (annualized). This is consistent in sign and magnitude with the basis-momentum factor, which is negatively exposed to volatility risk (see Panel B). The cross-sectional R^2's in these two models is about 0.65, which is not far below an R^2 of 0.85 for the two-factor model that includes the basis-momentum factor (see Table IV). This cross-sectional fit is impressive for a nontraded factor. When we control for the basis-momentum factor, however, the price of volatility risk is small and insignificant. We caution the reader not to interpret these joint regressions as horse races. As Cochrane (2005, ch. 7) notes, it is pointless to run horse races between models with nontraded factors and

[22] Each commodity-return observation is weighted by the inverse of lagged 12-month volatility. OLS coefficient estimates are similar and reported in Table IA.IX of the Internet Appendix.

Table IX

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 four models. The first and second models are two-factor models containing the average nearby factor (R^{nb}_{AVG}) and one of the volatility factors, that is, innovations in aggregate and average commodity market variance ($\Delta \text{var}^{mkt}_{t+1}$ and $\Delta \text{var}^{avg}_{t+1}$, respectively). In Models 3 and 4, we add the basis-momentum nearby factor (R^{nb}_{BM}). We regress the average returns of 32 commodity-sorted portfolios (that is, the nearby and spreading return of nine portfolios sorted on basis-momentum, basis, and momentum (the High4, Mid, and Low4 portfolio from these sorts) and seven sector portfolios (Energy, Grains, Industrial Materials, Meats, Metals, Oilseeds, and Softs)) on their full-sample exposures. In Panel A, 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 into the *MAPE* among nearby returns and spreading returns. Panel B presents the first-stage exposure from a time-series regression of the basis-momentum nearby factor on each volatility risk factor. The sample period is August 1960 through February 2014.

Panel A: Cross-Sectional Regressions

	γ_0	γ^{nb}_{AVG}	γ^{nb}_{BM}	γ^{mkt}_{var}	γ^{avg}_{var}	R^2 *MAPE*	$MAPE^{nb}$ $MAPE^{spr}$
Model 1	−1.41	6.60		−0.08		0.64	[3.27]
	(−4.37)	(3.58)		(−3.57)		[2.12]	[0.98]
Model 2	−1.11	6.48			−0.24	0.65	[3.13]
	(−3.09)	(3.49)			(−3.38)	[2.03]	[0.93]
Model 3	−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 4	−1.04	5.85	20.45		−0.08	0.86	[1.90]
	(−3.83)	(3.21)	(6.55)		(−1.21)	[1.29]	[0.68]

Panel B: Time-Series Exposure of $R^{nb}_{BM,t+1}$ to Volatility Risk

	$\Delta \text{var}^{mkt}_{t+1}$	$\Delta \text{var}^{avg}_{t+1}$
Exposure	−103.81	−33.81
	(−3.14)	(−2.63)

return-based mimicking portfolios of these factors. Rather, we interpret this evidence as supporting the interpretation that basis-momentum is a priced factor in commodity markets because it exposes investors to priced volatility risk.

To see why basis-momentum returns are increasing in lagged volatility but at the same time negatively exposed to volatility shocks, consider the definition of the futures price as the expected future spot price minus a risk premium (e.g., Fama and French (1987)). If this risk premium is increasing in volatility, then holding the expected spot price constant, a shock to volatility will decrease the futures price contemporaneously. French, Schwert, and Stambaugh (1987) analogously argue that when volatility predicts the equity premium with a positive sign in the time series, then holding future cash flows constant, the equity premium will be contemporaneously negatively exposed to volatility shocks.

D. Liquidity

The fact that basis-momentum is 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.[23] Following previous literature, we proxy for funding illiquidity using both the TED spread, the spread between the three-month certificate of deposit and the T-bill rate, and the implied volatility of S&P 100 index options (see, for example, Brunnermeier, Nagel, and Pedersen (2008), Nagel (2016), and Koijen et al. (2018)). We use the measure of Amihud (2002) aggregated across commodities to proxy for market illiquidity.

Panel A of Table X presents results of the portfolio-level asset pricing tests for these illiquidity risks. Together with the average commodity market factor, all four illiquidity proxies provide an adequate cross-sectional fit of around 0.70 driven by a large and significant price of risk. The estimates translate into a Sharpe ratio of about −0.60, which is consistent with basis-momentum in sign and magnitude, as this strategy is negatively exposed to innovations in illiquidity (see Panel D). Each illiquidity risk price is cut by more than half and insignificant when we control for basis-momentum. These findings are consistent with the idea that basis-momentum returns represent compensation for priced illiquidity risk, which is intimately related to volatility.

Table IA.X of the Internet Appendix presents additional evidence on the role of illiquidity from a double sort. Although Amihud illiquidity itself does not predict commodity returns in the cross section, the basis-momentum effect is about two-thirds higher for illiquid commodities. The fact that the basis-momentum effect is greater for commodities than for currencies and stock and bond indexes is also consistent with a liquidity story, as the average commodity in our sample is relatively illiquid. Finally, we note that Nagel (2012) argues that short-term reversal strategies capture the returns to liquidity provision in equity markets. Over our sample period, however, the correlation between the basis-momentum (nearby and spreading) factors and a short-term reversal factor is virtually zero.[24] We conclude that basis-momentum is related to illiquidity in dimensions that matter most for market-clearing in commodity markets, consistent with the idea that illiquidity is multidimensional.

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

[24] The short-term reversal factor is available from Kenneth French's data library.

Table X

Asset Pricing Tests for Illiquidity, Intermediary Capital, and Downside Market Risk

Panel A of this table tests whether four proxies of illiquidity risk are priced. The TED spread (a proxy for funding illiquidity) equals the three-month interbank LIBOR rate minus the three-month U.S. T-bill rate. The CDTB spread equals the three-month certificate of deposit rate minus the three-month U.S. T-bill rate. An aggregated Amihud measure proxies for market illiquidity. This measure is calculated as follows using daily first- and second-nearby returns and dollar volume ($R^{T_n}_{\text{fut},i,d}$ and $Vol^{T_n}_{i,d}$ for $n = 1, 2$). For each commodity, we calculate a backward-looking annual average of the daily measure: $R^{T_n}_{\text{fut},i,d}/Vol^{T_n}_{i,d}$. We then aggregate over all commodities i by separately taking 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 calculated as the average of the first- and second-nearby median Amihud measures. The VXO is the implied volatility of S&P100 index options, which is almost identical to the VIX, but available for a longer sample period. We take the first-differences in these illiquidity measures, denoted *TED*, *CDTB*, *AMI*, and *VXO*. Models 1 to 4 include the illiquidity risk factors next to the average nearby factor. Models 5 to 8 add the basis-momentum factor. Similarly, in Panel B we estimate the price of risk for exposure to the return of financial intermediaries (*FIR*) from He, Kelly, and Manela (2017) in Models 9 and 10. In Panel C, we test whether exposure to downside market risk is priced in Model 11 and control for the average commodity market and basis-momentum nearby factors in Model 12. These tests use two betas with respect to the CRSP value-weighted market portfolio: unconditional market beta, $\beta_{p,MKT} = \text{cov}(R_{p,t+1}, R_{MKT,t+1})/\text{var}(R_{MKT,t+1})$, and downside market beta, $\beta_{p,MKT^-} = \text{cov}(R_{p,t+1}, R_{MKT,t+1}|R_{MKT,t+1} < \mu - \sigma)/\text{var}(R_{MKT,t+1}|R_{MKT,t+1} < \mu - \sigma)$, where μ and σ are the average and standard deviation of $R_{MKT,t+1}$, respectively. Following Lettau, Maggiori, and Weber (2014), we fix the premium for unconditional market beta to the sample average market return. In all models, we regress average nearby and spreading returns of commodity portfolios sorted on basis-momentum, basis, and momentum (the High4, Mid, and Low4 portfolios 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. Panel D presents the first-stage exposure from a time-series regression of the basis-momentum nearby factor on each risk factor. The sample starts in February 1986 for illiquidity risk, January 1970 for intermediary capital risk, and August 1960 for downside market risk, dictated by data availability.

Panel A: Illiquidity Risk

	γ_0	$\gamma^{\text{nb}}_{\text{AVG}}$	γ^{nb}_{BM}	γ_{TED}	γ_{CDTB}	γ_{AMI}	γ_{VXO}	R^2 *MAPE*	*MAPE*$^{\text{nb}}$ *MAPE*$^{\text{spr}}$
Model 1	−1.84	5.56		−3.06				0.68	2.87
	(−3.32)	(2.27)		(−1.91)				[2.00]	[1.14]
Model 2	−1.83	5.92			−2.98			0.70	3.02
	(−3.98)	(2.37)			(−2.31)			[2.08]	[1.14]
Model 3	−0.80	6.16				−0.89		0.67	3.44
	(−1.18)	(2.50)				(−2.28)		[2.16]	[0.88]
Model 4	−1.34	4.98					−0.65	0.75	2.49
	(−1.89)	(1.99)					(−1.82)	[1.82]	[1.14]
Model 5	−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 6	−1.77	5.45	16.83		−1.20			0.88	1.57
	(−4.52)	(2.21)	(3.95)		(−1.10)			[1.21]	[0.85]

(*Continued*)

Table X—*Continued*

Panel A: Illiquidity Risk

	γ_0	γ_{AVG}^{nb}	γ_{BM}^{nb}	γ_{TED}	γ_{CDTB}	γ_{AMI}	γ_{VXO}	R^2 / $MAPE$	$MAPE^{nb}$ / $MAPE^{spr}$
Model 7	−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 8	−1.49	4.97	17.72				−0.27	0.89	1.41
	(−3.18)	(2.08)	(4.17)				(−1.12)	[1.13]	[0.84]

Panel B: Financial Intermediary Capital Risk

	γ_0	γ_{AVG}^{nb}	γ_{BM}^{nb}	γ_{FIR}	R^2 / $MAPE$	$MAPE^{nb}$ / $MAPE^{spr}$
Model 9	−1.05	5.97		−0.08	0.71	[3.06]
	(−2.47)	(2.76)		(−2.94)	[2.01]	[0.96]
Model 10	−1.03	6.14	19.78	−0.03	0.94	1.59
	(−3.39)	(2.90)	(6.14)	(−1.46)	(1.16)	[0.72]

Panel C: Downside Market Risk

	γ_0	γ_{AVG}^{nb}	γ_{BM}^{nb}	γ_{MKT}	γ_{MKT^-}	R^2 / $MAPE$	$MAPE^{nb}$ / $MAPE^{spr}$
Model 11	−1.66			6.16	21.38	0.57	4.00
	(−4.98)			(2.91)	(4.56)	[2.61]	[1.22]
Model 12	−0.83	2.74	19.64	6.16	7.31	0.90	1.88
	(−3.47)	(0.76)	(4.76)	(2.91)	(0.76)	[1.21]	[0.55]

Panel D: Time-Series Exposure of $R_{BM,t+1}^{nb}$ to risk factors

	ΔTED_{t+1}	$\Delta CDTB_{t+1}$	ΔAMI_{t+1}	ΔVXO_{t+1}	FIR_{t+1}	$R_{MKT,t+1}$	$R_{MKT,t+1} < \mu - \sigma$
Exposure	−2.87	−23.46	−8.59	−19.13	−43.15	−0.06	0.34
	(−1.71)	(−2.03)	(−1.79)	(−2.50)	(−0.87)	(−1.18)	(1.87)

E. Financial Intermediary Risk

The link to volatility and liquidity suggests an important role for financial intermediaries in explaining the basis-momentum effect. Adrian, Etula, and Muir (2014) and He, Kelly, and Manela (2017) find that intermediary risk factors are priced in many asset classes. Following He, Kelly, and Manela (2017), we analyze whether exposure to the value-weighted equity return of financial intermediaries (i.e., Primary Dealer counterparties of the New York Federal Reserve) is priced.[25] Panel B of Table X presents the results.

We see that the financial intermediary factor captures a large and significant premium when included next to the average commodity market factor, with an adequate R^2 of 0.71. The estimated price of risk is negative and translates into

[25] We thank the authors for sharing these data on their website.

a Sharpe ratio of −0.69. This estimate is consistent in sign and magnitude with Adrian, Etula, and Muir (2014) and thus theories of leverage-constrained intermediaries, such as Brunnermeier and Pedersen (2009) and Adrian and Shin (2014). In these theories the idea is that intermediaries borrow more in good times, and assets that pay off when leverage is low (and equity high) are attractive to hedge. Similar to volatility and illiquidity, basis-momentum is negatively exposed to financial intermediary risk (albeit insignificantly) and subsumes its pricing information in a joint test.

F. Downside Market Risk

Finally, we analyze the downside market risk measure of Lettau, Maggiori, and Weber (2014). The motivation here is that a speculator's commodity market-clearing ability may be impaired when the equity component of her portfolio is hit by a large negative shock. For this exercise, we use the CRSP value-weighted excess return ($R_{MKT,t+1}$) as the market and estimate an unconditional market beta as well as a market beta conditional on $R_{MKT,t+1}$ being less than one-standard-deviation below its mean. Panel C of Table X shows that downside market beta is priced at a large and significant premium of 21.38%, which is relative to 6.15% for unconditional market beta. Panel D shows that the basis-momentum factor has little exposure to the market unconditionally, but a larger and marginally significant exposure in low market return episodes. Consistent with this exposure, we find that downside market beta is driven out when we control for basis-momentum in the asset pricing test.

V. Extensions and Robustness Checks

In this section, we discuss additional analyses reported in the Internet Appendix.

A. Basis-Momentum across the Futures Curve

To start, we ask whether basis-momentum predictability is present throughout the futures curve. To answer this question, we first analyze whether basis-momentum, as measured in equation (3), is able to predict the returns of second- and third-nearby strategies ($R^{T_2}_{\text{fut},t+1}$ and $R^{T_3}_{\text{fut},t+1}$) as well as spreading returns between the second- and third-nearby and the third- and fourth-nearby strategies ($R^{T_2}_{\text{fut},t+1} - R^{T_3}_{\text{fut},t+1}$ and $R^{T_3}_{\text{fut},t+1} - R^{T_4}_{\text{fut},t+1}$). Next, we analyze whether alternative measures of basis-momentum, constructed using these farther-from-expiring strategies, contain orthogonal information about returns. Using notation similar to before, we define

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

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

Table IA.XI of the Internet Appendix reports average High4-minus-Low4 returns at different locations on the curve for sorts on these various basis-momentum signals.

In the first block of results, commodities are sorted on our original basis-momentum measure, BM_t. We find that farther-from-expiring futures returns are predictable using 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 $BM_t^{2,3}$ and $BM_t^{3,4}$. The first test in each block shows that these measures perform well in predicting returns of their respective contracts. For instance, sorting on $BM_t^{2,3}$ yields a High4-minus-Low4 Sharpe ratio of 0.92 and 0.68 for second-nearby and second-minus-third-nearby returns, respectively. To check 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 uses only those months in which $BM_t^{2,3}$ and $BM_t^{3,4}$ show little agreement with BM_t, that is, months in which three or fewer commodities (out of a total of eight in the High4 and Low4 portfolios combined) overlap between two alternative measures of basis-momentum. Even in these months with little agreement, the High4-minus-Low4 portfolios obtain considerable Sharpe ratios when investing in the farther-from-expiring strategies.

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 includes a maturity-specific component that varies across the short, mid, and long ends of the curve.

B. Composition and Stability of Basis-Momentum Portfolios

We next analyze the composition and stability of the sorts reported in Table I in the Internet Appendix. Figure IA.3 presents the percentage of months in which a given commodity is present in the High4 and Low4 portfolio, respectively. Relative to the case for basis, the basis-momentum and momentum strategies are more diverse in composition. Table IA.XII shows that on average roughly 3.25 (1.45) commodities stay (stay without requiring a roll-trade) in the High4 and Low4 basis-momentum portfolios in a given month. Again, these numbers are similar to momentum, while basis requires slightly more trading. Figure IA.4 shows that the basis-momentum effect weakens as time passes after sorting in month t, but remains significant for about a year. Figure IA.5 shows that the basis-momentum effect is driven by returns that are realized over the last year before portfolio formation. Table IA.XIII shows that the basis-momentum returns are robust to varying the number of commodities in the High and Low portfolios from one to eight.

C. Transaction Costs

Koijen et al. (2018) show that transaction costs subsume only a small part of the returns to basis strategies. Given that basis and momentum strategies are already applied in practice and are not too different in stability and composition from basis-momentum, it is unlikely that transaction costs subsume the large basis-momentum returns. More rigorously, consider the estimated average effective half-spread for large commodity futures trades of 4.4 basis points in Marshall, Nguyen, and Visaltanochoti (2012) (the estimated half-spread is even lower in Bollerslev et al. (2016) at 3.5 basis points). If we conservatively assume that basis-momentum requires the investor to turn over three of four commodities in the long and short positions 12 times per year, the total transaction costs would add up to $12 \times 2 \times 2 \times 0.75 \times 4.4 = 158.4$ basis points, which is well below average nearby returns of over 18%. Even spreading returns of around 4% likely survive this estimate, given that (i) spreading positions can be rebalanced with one trade using calendar spreads and (ii) Table I demonstrates that over 90% of the average spreading return of the High4-minus-Low4 basis-momentum strategy derives from the Low4 portfolio since 1986. Furthermore, basis-momentum predictability is not driven by the most illiquid commodities. Table IA.XIV presents results of commodity-level regressions and shows large effects from basis-momentum predictability in the time series of a large number of commodities from various sectors. Some represent large markets, such as crude oil, copper, and wheat.

D. Roll versus Spot Returns and Seasonalities

Table IA.XV shows that the average nearby return of the basis-momentum strategy is driven almost completely by roll returns (deriving from the shape of the futures curve), as spot returns are small and insignificant. This finding is perhaps unsurprising given that basis-momentum predicts spreading returns, which do not include a spot return component (see the discussion under equation (A8)). In Section IV.A, we conclude that the dynamics of storage and inventory are unlikely to explain basis-momentum. In line with this conclusion, Table IA.XVI shows that the basis-momentum effect is similar when we clean returns and the basis-momentum characteristic of seasonalities, even though there are large cross-sectional differences in the seasonal behavior of inventories due to variation in demand and supply.

VI. Conclusion

In this paper, we introduce basis-momentum, a signal related to the slope and curvature of the commodity futures curve. Basis-momentum has a number of important asset pricing implications. First, basis-momentum is an excellent predictor of commodity returns across many dimensions. Second, we find that exposure to a basis-momentum factor is priced and is a key determinant of cross-sectional variation in nearby and spreading commodity returns. We argue that classical theories based on storage and inventory dynamics or hedging pressure are unlikely to explain our results. Rather, basis-momentum is consistent with imbalances in supply and demand within and across the futures curve that materialize when the market-clearing ability of speculators and financial intermediaries is impaired. To this end, we show that the basis-momentum effect increases with volatility, illiquidity, and speculator spreading positions. Moreover, the risk premium that we estimate for basis-momentum is consistent in sign and magnitude with the pricing of volatility, liquidity, financial intermediary, and downside market risk.

Future work is warranted to find out how the positions of speculators and financial intermediaries relate to the separate components of basis-momentum, curvature and changes in slope, and to better understand why these components jointly are so strongly related to returns (in particular, relative to benchmark characteristics such as basis and momentum). We believe that maturity-specific position data, currently not publicly available from the CFTC, would be helpful to answer these questions.

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Appendix: Decomposing Nearby and Spreading Returns

Following Szymanowska et al. (2014), we define the futures price, $F_t^{T_n}$, in terms of the spot price of the underlying commodity, S_t, and the log or percentage basis, $y_t^{T_n}$:

$$F_t^{T_n} = S_t \exp\left(T_n \times y_t^{T_n}\right). \tag{A1}$$

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 $T_n = n$, so that the first-nearby return is based on 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 spot return can be decomposed into the spot premium, $\pi_{s,t}$, and the one-period basis, y_t^1:

$$\mathrm{E}_t[r_{s,t+1}] = \mathrm{E}_t[s_{t+1} - s_t] = \pi_{s,t} + y_t^1. \tag{A2}$$

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;

$$T_n \times y_t^{T_n} = y_t^1 + (T_n - 1)\mathrm{E}_t\left[y_{t+1}^{T_n - 1}\right] + \pi_{y,t}^{T_n}. \tag{A3}$$

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

$$\mathrm{E}_t\left[r_{fut,t+1}^1\right] = \mathrm{E}_t\left[s_{t+1} - f_t^1\right] = \mathrm{E}_t\left[s_{t+1} - s_t - y_t^1\right] = \pi_{s,t}. \tag{A4}$$

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, $\pi^2_{y,t}$. The expected return from an investment in the second-nearby futures contract equals

$$\mathrm{E}_t\left[r^2_{fut,t+1}\right] = \mathrm{E}_t\left[f^1_{t+1} - f^2_t\right] = \mathrm{E}_t\left[(s_{t+1} - s_t) + \left(y^1_{t+1} - 2y^2_t\right)\right], \tag{A5}$$

$$= \left(y^1_t + \pi_{s,t}\right) - \left(y^1_t + \pi^2_{y,t}\right) = \pi_{s,t} - \pi^2_{y,t}, \tag{A6}$$

such that

$$\mathrm{E}_t\left[r^{\mathrm{spr}}_{\mathrm{fut},t+1}\right] = \mathrm{E}_t\left[r^1_{\mathrm{fut},t+1}\right] - \mathrm{E}_t\left[r^2_{\mathrm{fut},t+1}\right] = \pi^2_{y,t}. \tag{A7}$$

It is interesting to separate 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:

$$\mathrm{E}_t\left[r^1_{\mathrm{fut},t+1}\right] = \mathrm{E}_t\left[r^{1,\mathrm{spot}}_{\mathrm{fut},t+1}\right] + \mathrm{E}_t\left[r^{1,\mathrm{roll}}_{\mathrm{fut},t+1}\right] = \left(\pi_{s,t} + y^1_t\right) + \left(-y^1_t\right), \tag{A8}$$

where the expected spot return is equal to $\mathrm{E}_t[r_{s,t+1}]$, and the roll return is the negative of the short-term basis. We do not decompose the expected spreading return because it does not include a spot return component. This result follows from the fact that the spot premium shows up in both the first- and the second-nearby returns, so that the expected spreading return contains only roll-return components. For the same reason, we do not decompose returns of farther-from-expiring contracts.

In the data, nearby returns to a rolling futures strategy are decomposed into their nontradable spot and roll-return components, as follows:

$$R^{\mathrm{spot}}_{\mathrm{fut},t+1} = \frac{1 + R^{T_1}_{\mathrm{fut},t+1}}{1 + R^{\mathrm{roll}}_{\mathrm{fut},t+1}} - 1, \tag{A9}$$

where

$$R^{\mathrm{roll}}_{\mathrm{fut},t+1} = \begin{cases} \frac{F^{T_1}_t}{F^{T_2}_t} - 1, & \text{if } T_1 = t+2, \\ 0, & \text{otherwise.} \end{cases} \tag{A10}$$

Equation (A9) shows that, by construction, the futures return combines the spot and the roll return. In months when the strategy rolls, the roll return is calculated by dividing the price of the contract rolled out of (the contract that expires in $t+2$) by the price of the contract rolled into (that expires after $t+2$). Roll returns are positive in backwardation and negative in contango.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.