Basis-momentum

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Journal of Finance forthcoming

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 the time series and 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 basis-momentum represents compensation for priced risk. Our findings are inconsistent with alternative explanations based on storage, inventory, and hedging pressure.

*Boons and Prado are with the Nova School of Business and Economics in Lisbon, Portugal. A previous version of this paper was circulated under the title "Basis-momentum in the futures curve and volatility risk." An Internet Appendix with supplementary results as well as replication data are found in the online version of this paper at the publisher's website. We thank Wei Xiong (the Editor), two anonymous referees, as well as Rui Albuquerque, Pedro Barroso, Magnus Dahlquist, Miguel Ferreira, Vincent van Kervel, Antonio Moreno, Andreas Neuhierl, Robert Richmond, Frans de Roon, Pedro Santa Clara, Ivan Shaliastovich, Kenneth Singleton, Marta Szymanowska, and Ke Tang for their helpful comments. We thank seminar participants at the Bocconi University, Commodity Market Workshop 2015 in Oslo, ECOMFIN 2016 in Paris, EFA 2016 in Oslo, FMA Annual Meeting 2016 in Las Vegas, Luxembourg School of Finance, NBER Commodity Workshop 2016, Nova School of Business and Economics, Spanish Finance Forum 2016 in Madrid, Stockholm School of Economics, Università Cattolica del Sacro Cuore, University of Kentucky, and 4Nations Cup in Lisbon. We are grateful to Marta Szymanowska for providing us with data. This work was funded by National Funds through FCT (Fundação para a Ciência e Tecnologia). We have read the *Journal of Finance*'s disclosure policy and have no conflicts of interest to disclose.

We introduce a characteristic, coined "basis-momentum," derived from the futures term structure. Basis-momentum is directly observable ex ante and is the strongest predictor of commodity returns to date across three key dimensions: the cross section, time series, and maturity. 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 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 markets. These asset pricing implications are important also for practitioners, because the recent financialization has inspired large and increasingly active institutional investment in commodities.[1]

Basis-momentum is measured as the difference between momentum in 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 natural that curvature positively predicts both nearby returns and spreading returns (from a long-short position in a nearby and a farther-from-expiring contract). Likewise, persistence in the steepening of the slope predicts nearby returns 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 curve (see Karstanje, van der Wel and van Dijk (2015)). Nevertheless, our evidence suggests that a single basis-momentum factor is the 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. Subsequent 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, e.g., Cochrane and Piazzesi (2008), Xiong and Yan (2010), and Campbell, Sunderam and Viceira (2016)).

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

Sorting 21 commodities since the inception of futures trading in 1959, we find a large average annualized difference between the high and low basis-momentum portfolio 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 to Sharpe ratios of 0.9 and respectively capture commodity spot and term premiums. 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) return 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]

Further 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 – that the difference between momentum measured at different points on the curve outperforms a single momentum measure – is supported in the data. Finally, evidence from first- to fourth-nearby contract returns suggests that basis-momentum predictability is maturity-specific.

The strength of basis-momentum predictability across all 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 a basis-momentum nearby and spreading factor. 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

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

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

the basis-momentum nearby factor captures priced risk orthogonal to the benchmark factors. The basis-momentum risk premium is close to the sample average return of the factor and translates to a Sharpe ratio ranging from 0.55 to 0.85 (depending on the specification). In fact, a two-factor model, including 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 what underlying economic sources can explain 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, which financial assets 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. For hedging pressure, we note that the principal ideas of Keynes and Cootner say little about maturity-specific effects. Moreover, basis-momentum is robust empirically to controlling for hedging pressure.

We also analyze explanations that rely on the market-clearing ability of speculators, and financial intermediaries more generally. We show that basis-momentum predictability is substantially stronger when speculators have many spreading positions. Such

[4] The theory of storage assumes that holders of inventories receive a convenience yield that declines as inventory increases, and 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.

"spreading pressure" also predicts commodity returns in isolation, which is a new result in the literature. The information 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 a directional exposure in times of high volatility. Also, Kang, Rouwenhorst and Tang (2016) argue that speculator's trades often take 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 (2009) 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 on positions that clear the market, and volatility increases. Conversely, liquidity declines when fundamental volatility increases. Because our results suggest that commodity-specific volatility is not driving 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. Thus, the evidence is 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, and these returns are 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, implying that investors are willing to pay for insurance against increases in volatility. The estimated risk-price is -0.65 in Sharpe ratio, consistent in size and sign 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 in-

[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. (2012a) for currencies.

terpretation that exposure to basis-momentum captures a premium, because it exposes investors to priced volatility risk.

These 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 multi-dimensional and unobservable (Brunnermeier, Nagel and Pedersen (2009) and Nagel (2012)). However, we show that popular proxies for market and funding liquidity risk are priced in commodity markets and, 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 (2016)) and downside market risk (Lettau, Maggiori and Weber (2014)). In isolation, both risk factors are priced in our cross section of commodities, consistent with previous evidence from a range of asset classes. Our risk-price estimates for the financial intermediary factor of He, Kelly and Manela (2016) 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 also 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. Further, 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]

[6]Bakshi, Gao and Rossi (2017) and Koijen et al. (2017) show that volatility risk is priced in a cross

I Data and variable definition

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 dataset is used in Szymanowska et al. (2014) to study 21 commodity futures from 1986 to 2010. We extend this dataset to start in July 1959, at the inception of futures trading, and to end in February 2014. We also add data for eleven commodities, including some large markets, such as natural gas.

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

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

where $F^{T_n}_{t+1}$ is the end-of-the-month price of the nth-nearby futures contract, 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 is sometimes observed. Although our tests focus on the more liquid first- and second-nearby contracts ($n = 1, 2$), we use third- and fourth-nearby contracts ($n = 3, 4$) in a robustness check.

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, $R^{T_1}_{fut,t+1}$. We refer henceforth to this nearby return as $R^{nb}_{fut,t+1}$. Term premiums are captured by a long-short position in the first-nearby contract and a farther-from-expiring contract. Henceforth, we use $R^{spr}_{fut,t+1}$ to refer to the (first-minus-

section of basis portfolios. He, Kelly and Manela (2016) show that financial intermediary risk is priced in a cross section of individual commodities in a relatively short sample over 2002-2012.

second-nearby) spreading return, $R^{T_1}_{fut,t+1} - R^{T_2}_{fut,t+1}$. Table IA.I of the Internet Appendix presents summary statistics for these commodity returns.

B Variable definition

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

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

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. Thus, basis and momentum are 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:

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

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 definition of first- and second-nearby log futures returns in Equations (A4)

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

and (A6) in the Appendix, and write basis-momentum as

$$\sum_{s=t-11}^{t} r^1_{fut,s} - \sum_{s=t-11}^{t} r^2_{fut,s} = \sum_{s=t-11}^{t} (s_s - f^1_{s-1}) - \sum_{s=t-11}^{t} (f^1_s - f^2_{s-1})$$
$$= \sum_{s=t-11}^{t} b^2_{s-1} - \sum_{s=t-11}^{t} b^1_s, \tag{4}$$

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 basis-momentum into a measure of average curvature ($\sum_{s=t-11}^{t-1} b^2_s - \sum_{s=t-11}^{t-1} b^1_s$) and a component that we interpret as a change in slope ($b^2_{t-12} - b^1_t$). For most observations in our sample, the curve is steeper on the short end, that is, $|b^2_t| < |b^1_t|$. 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={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

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

($R^{nb}_{BM,p,t+1}$ and $R^{spr}_{BM,p,t+1}$). Recall that expected nearby returns capture spot premiums, and expected spreading returns capture term premiums. As such, these sorts shed light on predictability 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]

[Insert Table I about here]

We conclude that all three signals contain information about nearby returns, but basis-momentum is the stronger predictor. 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 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 turn to pooled predictive regressions to show that the basis-momentum effect is robust to controlling for basis and momentum in a joint test:

$$\{R^{nb}_{fut,i,t+1}, R^{spr}_{fut,i,t+1}\} = \lambda'_C C_{i,t} + a_{t+1} + \mu_i + e_{i,t+1}. \tag{5}$$

[9] In the Internet Appendix, Table IA.II reports similar evidence for the larger set of 32 commodities and Table IA.III shows high basis-momentum returns in all ten-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).

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, thus controlling 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 for basis-momentum is positive and significant at 10.45 ($t = 7.45$), which translates to 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 impact 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 ($t = 6.81$), thus 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 this joint test.

[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 by and large identical.

[Insert Table II about here]

Panel B shows similarly strong evidence for basis-momentum predictability in spreading returns. In isolation (column (1)), the coefficient estimate for basis-momentum is positive and significant at 2.34 ($t = 6.89$), which translates to 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 shows similar evidence for the larger cross section of 32 commodities, even in a specification that includes month×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 shows 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 the notation in Section I.B are defined as:

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

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

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

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

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, denoted R^{nb}_{BM} and R^{spr}_{BM}. 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^{nb}_{B}); (ii) the spreading return of the High4 portfolio ($R^{spr}_{B,High4}$); and (iii) the spreading return of the Low4 portfolio ($R^{spr}_{B,Low4}$). 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 of all commodities, R^{nb}_{AVG}); (ii) R^{nb}_{B} as in Szymanowska et al. (2014); and (iii) the High4-minus-Low4 momentum portfolio (R^{nb}_{M}). 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, whereas standard deviation, skewness, and kurtosis are similar to the benchmark factors. These higher moments thus 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.

[Insert Table III about here]

A Time series tests

In recent work, Barillas and Shanken (2017a, 2017b) 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^{nb}_{BM} is high and significant in both models at about 13% ($t > 5$), down from 18% in average returns. Similarly, the alpha of R^{spr}_{BM} 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 the conclusion 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 asks whether the benchmark factors of Szy-

[12] Table IA.V of the Internet Appendix shows that these conclusions are robust for 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 of 21 commodities into two portfolios, split at the median of each characteristic.

manowska 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., $R^{spr}_{B,Low4}$) 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 $R^{spr}_{B,Low4}$ 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. Therefore, we interpret this evidence as indicating that the four-factor model contains all economically relevant pricing information.

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, which is our primary interest. The reason is that relatively little is known about the cross section of commodities, such that there is lots 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 the previous evidence, we consider six candidate models nested in:

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

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 specification add the basis-momentum nearby factor to these 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. The motivation is that investors in commodity markets often take positions farther down the futures curve, 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 roll-over 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 sixteen portfolios sorted on basis, momentum, basis-momentum, and sector.[13] For 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

[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.

arguments in the literature to run cross-sectional tests for individual stocks rather than portfolios (see, e.g., 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.

Table IV presents annualized risk-price estimates. For the portfolio-level test in Panel A, each estimate is accompanied by two t-statistics, estimated using either Shanken (1992) standard errors (t_S, robust to errors-in-variables in the first-stage betas) 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 sixteen nearby-portfolio returns and the sixteen spreading-portfolio returns ($MAPE^{nb}$ and $MAPE^{spr}$). 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.

[Insert Table IV about here]

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 specification show that the basis-momentum nearby factor is significantly priced

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

when added to each of these benchmark models at about 18% ($t_{KRS} > 3.5$), which translates to 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^2's ($MAPE$'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 the larger 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 specification six gives a slightly better cross-sectional fit ($R^2 = 0.92$ and $MAPE = 1.00\%$). There is at the same time 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 larger three- and four-factor models. Among the remaining factors, the basis and average nearby factor are consistently priced, but the momentum nearby factor is not. The intuition behind the result for momentum is that a commodity with high past twelve-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 interpretation as a true risk factor. Finally, the estimated intercept is economically small in all specifications, although it is significant in some portfolio-level test 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 an excellent cross-sectional fit. Figure IA.2 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 specifications four and six) provide a 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 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 test what underlying economic sources might be driving the effect. 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.

[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 of the Internet Appendix); and (iii) use the High-minus-Low factors that are split at the median (see Panel C of Table IA.VII).

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 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 to reflect a spot price increase due to a shortage of goods, and the futures price may fall below the spot price. Therefore, the convenience yield is 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 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, for which exercise we split the sample into "more" and "less" storable commodities, motivated by the idea that inventory dynamics are more relevant for commodities that are difficult to store.[17]

[**Insert Table V about here**]

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 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.

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

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

A.2 Basis-momentum in alternative asset classes

We next test whether there is a basis-momentum effect in three alternative asset classes. Section A 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, $R^1_{cur,t+1} = S_{t+1}/F^1_t - 1$, and spreading return, $R^1_{cur,t+1} - (F^1_{t+1}/F^2_t - 1)$. The sample of stock indexes includes twelve 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 ten markets. As in Koijen et al. (2017), we calculate synthetic returns for a one- and six- month futures contract on a ten-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 in a High4 and Low4 portfolio using basis-momentum, basis, and momentum.

Table VI presents the results for currencies in Panel A. Currency returns monotonically increase 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 to 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 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.

[Insert Table VI about here]

Panel B shows that stock index returns also monotonically increase 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 to 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 Sharpe ratio of 0.52. Because our focus is on commodity markets, we leave a thorough investigation of basis-momentum in these alternative asset classes to future work. Yet, 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 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 non-commercial spreading positions as a fraction of open interest. Spreading positions measure the extent to which an individual non-commercial 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 twelve-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 captured well by the high-frequency fluctuations in observed monthly hedging pressure.[18] Empirically, we find that twelve-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.

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.

[Insert Table VII about here]

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

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

where $I_{HP,i,t}$ and $I_{SP,i,t}$ are dummies that equal 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,

[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, is shortcomings in the hedger classification by the CFTC (see, e.g., Acharya, Lochstoer and Ramadorai (2013), and Dewally, Ederington and Fernando (2013)).

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 8.67% without controls. 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 the decision of speculators 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, which 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] Further, speculators, and financial intermediaries more generally, might be averse to taking a directional exposure to the commodity in times of high uncertainty and thus opt for

[20]Table IA.VIII 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.

a spreading position. This idea is implicit in classical inventory models, such as Stoll (1978), where 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.

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 (2009), 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, var_t^{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, var_t^{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:

$$\{R^{nb}_{p,t+1:t+k}, R^{spr}_{p,t+1:t+k}\} = v_0 + v_1 var_t + e_{t+1:t+k}, \tag{10}$$

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

[Insert Table VIII about here]

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 in high volatility months and normal

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

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 the 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 asset pricing tests for volatility risk using the cross section of nearby and spreading returns of sixteen 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: Δvar^{mkt}_{t+1} and Δvar^{avg}_{t+1}.

[Insert Table IX about here]

We find that exposure to volatility risk captures a large and significant negative price of risk. The point estimates translate to 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^2s 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 non-traded factor. When we control for the basis-momentum factor, however, the price of volatility risk is small and insignificant. We caution 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 non-traded factors and 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 motivate why basis-momentum returns are increasing in lagged volatility, but contemporaneously 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, holding the expected spot price constant, a shock to volatility will lower 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, holding future cash flows constant, the equity premium will be negatively exposed to volatility shocks contemporaneously.

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 with 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, e.g., Brunnermeier, Nagel and Pedersen (2009), Nagel (2016), and Koijen et al. (2017)). An Amihud (2002) measure aggregated across commodities proxies for market illiquidity.

Panel A of Table X presents the portfolio-level asset pricing tests for these illiquidity risks. Together with the average commodity market factor, all four illiquidity proxies

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

provide an adequate cross-sectional fit of around 0.70 driven by a large and significant price of risk. The estimates translate to 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 more than cut in 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 risk factor is intimately related to volatility.

[**Insert Table X about here**]

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 higher by about two-thirds 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. Yet, over our sample period, 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 multi-dimensional.

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 (2016) find that intermediary risk factors are priced in many asset classes. Following He, Kelly and Manela (2016), we analyze whether exposure to the

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

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 to 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 is that speculator's commodity-market clearing ability may be impaired when the equity component of their 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 lower 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.

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

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 ($R^{T_2}_{fut,t+1}$ and $R^{T_3}_{fut,t+1}$) as well as spreading returns between the second- and third-nearby and the third- and fourth-nearby strategies ($R^{T_2}_{fut,t+1} - R^{T_3}_{fut,t+1}$ and $R^{T_3}_{fut,t+1} - R^{T_4}_{fut,t+1}$). 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

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

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

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 $BM^{2,3}_t$ and $BM^{3,4}_t$. The first test in each block shows that these measures perform well in predicting returns of their respective contracts. For instance, sorting on $BM^{2,3}_t$ yields a High4-minus-Low4 Sharpe ratio of 0.92 and 0.68 for second-nearby and second-minus-third-nearby returns, respectively. To ascertain that this result is not driven by a large correlation between basis-momentum measured at different points on the futures curve, the second test in each block uses only those months where $BM_t^{2,3}$ and $BM_t^{3,4}$ show little agreement with BM_t. Specifically, months with little agreement are those when less than or equal to three commodities (of a total of eight in the High4 and Low4 portfolio 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 end of the curve.

B Composition and stability of basis-momentum portfolios

We analyze the composition and stability of the sorts reported in Table I. Figure IA.3 shows the percentage of months in which a given commodity is present in the High4 and Low4 portfolio, respectively. Relative to the case of basis, the basis-momentum and momentum strategies are more diverse in composition. 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 portfolio 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 until 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 robust basis-momentum returns when varying the number of commodities in the High and Low portfolio from one to eight.

C Transaction costs

Koijen et al. (2017) 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 out of four commodities in the long and short position twelve times per year, the total transaction cost 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 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 almost completely driven 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

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 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 available publicly from the CFTC, would be helpful to answer these questions.

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:

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

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,

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

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

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

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:

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

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

such that

$$E_t[r^{spr}_{fut,t+1}] = E_t[r^1_{fut,t+1}] - E_t[r^2_{fut,t+1}] = \pi^2_{y,t}. \tag{A7}$$

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:

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

where the expected spot return is equal to $E_t[r_{s,t+1}]$, and the roll return is the negative of the short-term basis. We do not decompose the expected spreading return, because it does not include a spot return component. This result follows from the fact that the spot premium shows up in both the first- and second-nearby return, 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 non-tradable spot and roll return components, as follows:

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

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

Equation (A9) expresses 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.

References

Acharya, Viral V., Lars A. Lochstoer, and Tarun Ramadorai, 2013, Limits to arbitrage and hedging: Evidence from commodity markets, *Journal of Financial Economics* 109, 441-465.

Adrian, Tobias, Erkko Etula, and Tyler Muir, 2014, Financial intermediaries and the cross-section of asset returns, *Journal of Finance* 69, 2557-2596.

Adrian, Tobias, and Joshua Rosenberg, 2008, Stock returns and volatility: Pricing the short-run and long-run components of market risk, *Journal of Finance* 63, 2997-3030.

Adrian, Tobias, and Hyuan Song Shin, 2014, Procyclical leverage and value-at-risk, *Review of Financial Studies* 27, 373-403.

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross section and time series effects, *Journal of Financial Markets* 5, 31-56.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259-299.

Ang, Andrew, Jun Liu, and Krista Schwarz, 2011, Using stocks or portfolios in tests of factor models, Working Paper, Columbia University.

Bakshi, Gurdip, Xiaohui Gao, and Alberto Rossi, 2017, Understanding the sources of risk underlying the cross section of commodity returns, *Management Science*, Forthcoming.

Barillas, Francisco, and Jay A. Shanken, 2017a, Which alpha?, *Review of Financial Studies*, Forthcoming.

Barillas, Francisco, and Jay A. Shanken, 2017b, Comparing asset pricing models, *Journal of Finance*, Forthcoming.

Basak, Suleyman, and Anna Pavlova, 2016, A model of financialization of commodities, *Journal of Finance* 71, 1511-1556.

Bollerslev, Tim, Benjamin Hood, John Huss, and Lasse H. Pedersen, 2016, Risk everywhere: Modeling and managing volatility, Working paper, Duke University.

Brunnermeier, Markus K., Stefan Nagel, and Lasse H. Pedersen, 2009, Carry trades and currency crashes, *NBER Macroeconomics Annual 2008* 23, 313-347.

Brunnermeier, Markus K., and Lasse H. Pedersen, 2009, Market liquidity and funding liquidity, *Review of Financial Studies* 22, 2201-2238.

Campbell, John Y., Adi Sunderam, and Luis M. Viceira, Inflation bets or deflation hedges? The changing risks of nominal bonds, *Critical Finance Review*, Forthcoming.

Cheng, Ing-Haw., Andrei Kirilenko, and Wei Xiong, 2015, Convective risk flows in commodity futures markets, *Review of Finance* 19, 1733-1781.

Cochrane, John H., 2005, Asset pricing - revised edition, Princeton: Princeton University press.

Cochrane, John H., and Monika Piazzesi, 2005, Bond risk premia, *American Economic Review* 95, 138-60.

Cochrane, John H., and Monika Piazzesi, 2008, Decomposing the yield curve, Working paper, University of Chicago.

Cootner, Paul H., 1960, Returns to speculators: Telser vs. Keynes, *Journal of Political Economy* 68, 396-404.

Cootner, Paul H., 1967, Speculation and hedging, *Food Research Institute Studies* 7, 65-106.

Daskalaki, Charoula, Alexandros Kostakis, and George Skiadopoulos, 2014, Are there common factors in commodity futures returns? *Journal of Banking and Finance* 40, 346-363.

Deaton, Angus, and Guy Laroque, 1992, On the behavior of commodity prices, *Review of Economic Studies* 59, 1-23.

Dewally, Michael, Louis H. Ederington, and Chitru S. Fernando, 2013, Determinants of trader profits in commodity futures markets, *Review of Financial Studies* 26, 2648-2683.

Fama, Eugene F., and Kenneth R. French, 1987, Commodity futures prices: Some evidence on forecast power, premiums, and the theory of storage, *The Journal of Business* 60, 55-73.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fama, Euegene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: empirical tests, *Journal of Political Economy* 81, 607-636.

French, Kenneth R., G. William Schwert, and Robert F. Stambaugh, 1987, Expected stock returns and volatility, *Journal of Financial Economics* 19, 3-29.

Gibbons, Michael R., Stephen A. Ross, and Jay Shanken, 1989, A test of the efficiency of a given portfolio, *Econometrica* 57, 1121-1152.

Gorton, Gary B, Fumio Hayashi, and K. Geert Rouwenhorst, 2012, The fundamentals of commodity futures returns, *Review of Finance* 17, 35-105.

Guo, Hui, 2006, On the out-of-sample predictability of stock market returns, *Journal of Business*, 79, 645-70.

He, Zhiguo, Bryan Kelly, and Asaf Manela, Intermediary asset pricing: New evidence from many asset classes, *Journal of Financial Economics*, Forthcoming.

Kaldor, Nicholas, 1939, Speculation and economic stability, *Review of Economic Studies* 7, 1-27.

Kan, Raymond, Cesare Robotti, and Jay Shanken, 2013. Pricing model performance and the two-pass cross-sectional regression methodology. *Journal of Finance* 68, 2617-2649.

Kang, Wenjin, K. Geert Rouwenhorst, and Ke Tang, 2016, A Tale of Two Premiums: The role of hedgers and speculators in commodity futures markets, Working Paper, Yale University.

Karstanje, Dennis, M., Michel van der Wel, and Dick van Dijk, 2015, Common factors in commodity futures curves, Working Paper, Erasmus School of Economics.

Keynes, John Maynard, 1930, Treatise on Money, London: Macmillan.

Koijen, Ralph S.J., Toby J. Moskowitz, and Lasse H. Pedersen, E.B. Vrugt, 2017, Carry, *Journal of Financial Economics*, Forthcoming.

Lettau, Martin, Matteo Maggiori, and Michael Weber, 2014, Conditional risk premia in currency markets and other asset classes, *Journal of Financial Economics* 114, 197-225.

Lewellen, Jonathan, Stefan Nagel, and Jay Shanken, 2010, A skeptical appraisal of asset pricing tests, *Journal of Financial Economics* 96, 175-194.

Lustig, Hanno, Nikolai Roussanov, and Adrien Verdelhan, 2011, Common risk factors in currency markets, *Review of Financial Studies* 24, 3731-3777.

Lustig, Hanno, Nikolai Roussanov, and Adrien Verdelhan, 2013, Countercyclical currency risk premia, *Journal of Financial Economics* 111, 527-553.

Marshall, Ben R., Nhut H. Nguyen, and Nuttawat Visaltanochoti, 2012, Commodity liquidity measurement and transaction costs, *Review of Financial Studies* 25, 599-638.

Menkhoff, Lukas, Lucio Sarno, Maik Schmeling, and Andreas Schrimpf, 2012a, Carry trades and global foreign exchange volatility, 2012, *Journal of Finance* 67, 681-718.

Menkhoff, Lukas, Lucio Sarno, Maik Schmeling, and Andreas Schrimpf 2012b, Currency momentum strategies, *Journal of Financial Economics* 106, 660-684.

Miffre, Joelle, 2013, Comparing first, second and third generation commodity indices, Working paper, EDHEC School of Business.

Moskowitz, Tobias J., Yao H. Ooi, and Lasse H. Pedersen, 2012, Time series momentum, *Journal of Financial Economics* 104, 228-250.

Nagel, Stefan, 2012, Evaporating liquidity, *Review of Financial Studies* 25, 2005-2039.

Nagel, Stefan, 2016, The liquidity premium of near-money assets, *Quarterly Journal of Economics* 131, 1927-1971.

Shanken, Jay., 1992, On the estimation of beta-pricing models, *Review of Financial Studies* 5, 1-33.

Sockin, Michael, and Wei Xiong, 2015, Informational frictions and commodity markets, *Journal of Finance* 70, 2063-2098.

Stoll, Hans R., 1978, The supply of dealer services in securities markets, *Journal of Finance* 33, 1133-1151.

Szymanowska, Marta, Frans A. de Roon, Rob van der Goorbergh, and Theo Nijman, 2014, An Anatomy of Commodity Futures Risk Premia, *Journal of Finance* 69, 453-483.

Tang, Ke, and Wei Xiong, 2012, Index Investing and the Financialization of Commodities, *Financial Analysts Journal* 68, 54-74.

Working, Holbrook, 1949, The theory of the price of storage, *American Economic Review* 39, 1254-1262.

Wright, Jonathan H., 2011, Term premia and inflation uncertainty: Empirical evidence from an international panel dataset, *American Economic Review* 101, 1514-1534.

Xiong, Wei, and Hongjun Yan, 2010, Heterogeneous expectations and bond markets, *Review of Financial Studies* 23, 1433-1466.

Yang, Fan, 2013, Investment shocks and the commodity basis spread, *Journal of Financial Economics* 110, 164-184.

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: $\prod_{s=t-11}^{t}(1+R_{fut,s}^{T_1}) - \prod_{s=t-11}^{t}(1+R_{fut,s}^{T_2})$) as well as basis ($F_t^{T_2}/F_t^{T_1}-1$) and momentum ($\prod_{s=t-11}^{t}(1+R_{fut,s}^{T_1})$) as a benchmark. The High4 and Low4 portfolio contain the top and bottom four ranked commodities, respectively, whereas the Mid portfolio contains all remaining commodities (which number is time-varying). In each post-ranking month $t+1$, the portfolio's nearby return is the equal-weighted average return of first-nearby contracts ($R_{p,t+1}^{nb} = R_{p,t+1}^{T_1}$), whereas the spreading return is the equal-weighted average of the difference between the return of the first-nearby and second-nearby contract ($R_{p,t+1}^{spr} = R_{p,t+1}^{T_1} - R_{p,t+1}^{T_2}$). 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 ($R_{p,t+1}^{nb}$)						
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 ($R_{p,t+1}^{spr}$)						
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

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) has 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. t-statistics are presented underneath each estimate and are calculated using standard errors clustered in the time dimension. Panel C presents results for two decompositions of basis-momentum over the full sample period. In the left block of results, we regress 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 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 at 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 ($R^{nb}_{fut,i,t+1}$)									
λ_{BM}	10.45	9.55	10.25	9.16			9.19	10.63	8.22
(t)	(7.45)	(7.23)	(7.06)	(6.81)			(6.22)	(4.64)	(4.09)
λ_B					-5.89		3.47	5.41	3.64
(t)					(-2.16)		(1.14)	(1.06)	(0.96)
λ_M						1.01	0.33	0.36	0.13
(t)						(2.32)	(0.66)	(0.45)	(0.20)
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 ($R^{spr}_{fut,i,t+1}$)									
λ_{BM}	2.34	1.94	2.16	1.71			2.33	1.44	2.75
(t)	(6.89)	(5.63)	(6.30)	(4.89)			(6.71)	(3.27)	(5.10)
λ_B					0.26		0.99	-0.03	1.86
(t)					(0.24)		(0.89)	(-0.02)	(1.21)
λ_M						-0.16	-0.33	-0.33	-0.31
(t)						(-1.22)	(-2.35)	(-1.30)	(-2.45)
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	0.04	0.02	0.05

Panel C: Decomposing basis-momentum predictability

	$R^{bn}_{fut,i,t+1}$	$R^{spr}_{fut,i,t+1}$		$R^{nb}_{fut,i,t+1}$	$R^{spr}_{fut,i,t+1}$
λ_M	9.06	1.87	λ_{Curv}	6.08	1.64
(t)	(6.65)	(5.67)		(6.24)	(6.07)
$\lambda_M^{T_2}$	-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

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 ($R^{spr}_{B,High4}$), and (iii) the spreading return of the Low4 portfolio ($R^{spr}_{B,Low4}$)); 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 spanning tests that ask 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

	Avg. ret.	St. dev.	Skew.	Kurt.	AR(1)	Correlations R^{nb}_{BM}	R^{nb}_{B}	R^{nb}_{AVG}	R^{nb}_{M}	R^{spr}_{BM}	$R^{spr}_{B,High4}$
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		
$R^{spr}_{B,High4}$	-1.11	2.50	0.23	5.55	0.11	-0.19	0.36	0.14	-0.15	-0.29	
$R^{spr}_{B,Low4}$	-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}	$\beta^{spr}_{B,High4}$	$\beta^{spr}_{B,Low4}$	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}

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 Low4 basis portfolio ($R_{B,High4}^{spr}$ and $R_{B,Low4}^{spr}$). The second model of Bakshi, Gao and Rossi (2017) contains three nearby factors: a market index ("the average factor", R_{AVG}^{nb}), a basis factor (R_B^{nb}), and a momentum factor (R_M^{nb}). The third and fourth model 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 factor 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 return of 9 portfolios sorted on basis-momentum, basis, and momentum (the High4, Mid, and Low4 portfolio from each of these sorts) and 7 sector portfolios (Energy, Grains, Industrial Materials, Meats, Metals, Oilseeds, and Softs). The commodity-level test in Panel B conducts monthly Fama and MacBeth (1973) cross-sectional regressions of the nearby and spreading returns of 21 commodities on their historical exposure, estimated over a one year rolling window of daily returns. Due to the staggered introduction of commodities in the sample, the size of the cross-section is 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 in the $MAPE$ among nearby returns and spreading returns. These measures follow from a regression of average returns on full sample betas in Panel A and average returns on average betas in Panel B. We present results for the full sample period from August 1960 through February 2014, but also summarize the evidence for two subsamples (split at January 1986 and focusing on the price of risk for the nearby basis-momentum factor and the cross-sectional fit).

Table IV continued

					Full sample						Pre-1986		Post-1986	
	γ_0	γ^{nb}_{BM}	γ^{nb}_{B}	γ^{nb}_{AVG}	γ^{nb}_{M}	γ^{spr}_{BM}	$\gamma^{spr}_{B,High4}$	$\gamma^{spr}_{B,Low4}$	R^2 $MAPE$	$MAPE^{nb}$ $MAPE^{spr}$	γ^{nb}_{BM}	R^2 $MAPE$	γ^{nb}_{BM}	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>									
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]
	<0.28>	<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]

Table V: Double sorts: Basis-momentum versus inventory-related variables
This table presents average nearby (Panel A) and spreading (Panel B) returns when we 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); and, storability (splitting the sample into 17 "less" and 15 "more" storable commodities). For the sake of comparison, the first two columns present the single sort on each of these variables. The last six columns present the double sort, with the last two columns containing the High-Low basis-momentum return in each control group. In each post-ranking month $t + 1$, the portfolio's nearby return is the equal-weighted average return of first-nearby contracts, whereas the spreading return is the equal-weighted average of the difference between the return of the first-nearby and second-nearby contract. We present results for the full sample period (using only those months where we have at least 8 commodities with available data) with one exception: the sample for inventory runs from 1970 through 2010 as in Gorton, Hayashi and Rouwenhorst (2012).

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 ($R^{nb}_{p,t+1}$)									
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)		
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 ($R^{spr}_{p,t+1}$)									
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)		

Table VI: 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 A 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 analogous to 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 portfolio 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 period runs from April 1997 through August 2015, the stock index sample period 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 ($R^1_{cur,p,t+1}$)						
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 ($R^1_{cur,p,t+1} - R^2_{cur,p,t+1}$)						
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 ($R^{T_1}_{stock,p,t+1}$)						
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 ($R^{T_1}_{stock,p,t+1} - R^{T_2}_{stock,p,t+1}$)						
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
Panel C: Bond indexes						
Nearby returns ($R^1_{bond,p,t+1}$)						
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

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 non-commercials (speculators) as a fraction of open interest. For this analysis, we take a twelve-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 present results from pooled regressions for both nearby and spreading returns. For this regression, HP and SP are converted to 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 independent variable. Model (2) adds the position dummies. Model (3) adds the interaction effects. All regressions include time fixed effects and 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 ($R^{nb}_{fut,i,t+1}$)			Spreading returns ($R^{spr}_{fut,i,t+1}$)		
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

Table VIII: Does volatility predict basis-momentum returns?

This table analyzes whether basis-momentum returns are increasing in lagged volatility. Aggregate commodity market variance, var_t^{mkt}, is calculated as the sum of squared daily returns on an equal-weighted commodity index, and average commodity market variance, var_t^{avg}, is calculated as the equal weighted average of the sum of squared daily returns of individual commodities. Panel A presents coefficient estimates, v_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 ($R^{nb}_{p,t+1:t+k}$) and spreading ($R^{spr}_{p,t+1:t+k}$) 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 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				6	12	12	12
	High4	Mid	Low4	H4-L4	H4-L4	H4-L4	H4-L4	H4-L4
				Nearby returns ($R^{nb}_{p,t+1:t+k}$)				
v_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
v_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 ($R^{spr}_{p,t+1:t+k}$)				
v_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
v_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 vs. 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

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 model 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 (Δvar^{mkt}_{t+1} and Δvar^{avg}_{t+1}, respectively). In models three and four, 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 9 portfolios sorted on basis-momentum, basis, and momentum (the High4, Mid, and Low4 portfolio from these sorts) and 7 sector portfolios (Energy, Grains, Industrial Materials, Meats, Metals, Oilseeds, and Softs)) on their full sample exposures. We present in Panel A 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 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 from 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

	Δvar^{mkt}_{t+1}	Δvar^{avg}_{t+1}
Exposure	-103.81	-33.81
	(-3.14)	(-2.63)

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 3-month interbank LIBOR rate minus the 3-month US t-bill rate. The CDTB spread equals the three-month certificate of deposit rate minus the 3-month US 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 ($R^{T_n}_{fut,i,d}$ and $Vol^{T_n}_{i,d}$ for $n = 1, 2$). For each commodity, we calculate a backward-looking annual average of the daily measure: $R^{T_n}_{fut,i,d}/Vol^{T_n}_{i,d}$. We then aggregate over all commodities i by taking separately the median of first- and second-nearby contracts to deal with outliers and the fact that first-nearby contracts are typically more liquid. Then, the aggregate commodity-market Amihud-measure is the average of the first- and second-nearby median Amihud-measure. 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 then 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 (2016) 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, $\beta_{p,MKT} = cov(R_{p,t+1}, R_{MKT,t+1})/var(R_{MKT,t+1})$, and downside market beta, $\beta_{p,MKT^-} = cov(R_{p,t+1}, R_{MKT,t+1}|R_{MKT,t+1} < \mu - \sigma)/var(R_{MKT,t+1}|R_{MKT,t+1} < \mu - \sigma)$, 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 portfolio from these sorts) on their full sample exposures. We present the estimated prices of risk (γ) with corresponding Shanken (1992) t-statistics in parentheses underneath each estimate. Also, we present the cross-sectional R^2 and the mean absolute pricing error ($MAPE$, in brackets), which is further decomposed in the $MAPE$ among nearby returns and spreading returns. 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.

Table X continued

Panel A: Illiquidity risk

	γ_0	γ^{nb}_{AVG}	γ^{nb}_{BM}	γ_{TED}	γ_{CDTB}	γ_{AMI}	γ_{VXO}	R^2 $MAPE$	$MAPE^{nb}$ $MAPE^{spr}$
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]
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^{nb}_{AVG}	γ^{nb}_{BM}	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^{nb}_{AVG}	γ^{nb}_{BM}	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 $R^{nb}_{BM,t+1}$ 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)

Internet Appendix for "Basis-momentum"

MARTIJN BOONS and MELISSA PRADO*

This internet appendix describes the data we use in our tests for financial assets (Section A) and presents the figures mentioned in the paper as well as tables with a number of robustness checks (Section B).

A Currency, stock index, and bond index data

To be consistent with a large body of literature on currencies, the currency return data is constructed using forward exchange rates. Our spot as well as one- and two-month forward exchange rates (in US dollars per unit of foreign currency) cover the sample period from December 1996 to August 2015, and are obtained from BBI and Reuters (via Datastream). Although for many currencies spot and one-month forward exchange rates are available before 1996, two-month forward exchange rates are not. Spot and forward rates are observed on the last trading day of a given month. Our total sample consists of the following 48 countries: Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Egypt, Euro area, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Iceland, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Ukraine, United Kingdom. These countries are equally split into developed and emerging markets as classified by Dow Jones (`https://en.wikipedia.org/wiki/Developed_market`).

*Boons, Martijn, and Melissa Prado, Internet Appendix to "Basis-momentum," *Journal of Finance* [DOI STRING]. Please note: Wiley-Blackwell is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing material) should be directed to the authors of the article.

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

In each month t, we define currency basis-momentum, basis, and momentum as follows:

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

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

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

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

Similar to Moskowitz, Ooi and Pedersen (2012) and Koijen et al. (2017), we collect a sample of twelve stock indexes with futures data available from the CRB or in Datastream: United States (S&P500), United Kingdom (FTSE), Germany (DAX), Italy (MIB-mini), Japan (TOPIX), Australia (ASX), Netherlands (AEX), France (CAC40), Finland (OMX), Spain (IBEX-mini), Switzerland (SMI), and Hong Kong (Hang Seng). We construct first- and second-nearby stock index futures returns following the same procedure as described in Section I.A for commodities. Koijen et al. (2017, Appendix A) show that returns in the foreign currency closely approximate the dollar return of a fully-collateralized, currency-hedged investment in a foreign currency-dominated futures contract.[1] We also define basis-momentum, basis, and momentum as described in Section I.B. Most stock indexes trade only contracts with maturities in March, June, September, or December, especially in the earlier part of the sample. To be consistent over the full sample period and across indexes, we use only these four maturities. We check that the correlation between each first-nearby stock index futures return and the corresponding cash index return is almost perfect. For our sort, we use all months with at least eight stock indexes with available first- and second-nearby data. This leaves us with a final sample of 144 months (out of the available 149 months) over the period from August 2002 to December 2014.

Following Koijen et al. (2017), we construct a sample of synthetic futures returns on government bonds from the United States, Australia, Canada, Germany, the United Kingdom, Japan, New Zealand, Norway, Sweden, and Switzerland. We collect the constant maturity zero coupon yields from Wright (2011), which data is available until May 2009.[2] Each month, we calculate the price of two synthetic futures on the ten year zero coupon bond (with spot price $S_t^{120} = \frac{1}{(1+y_t^{120})^{120}}$) with expiration in one and six months, respectively:

$$F_t^1 = S_t^{120}(1 + y_t^1), \text{ and} \tag{IA.4}$$

$$F_t^6 = S_t^{120}(1 + y_t^6)^6. \tag{IA.5}$$

At expiration, the price of the one month futures contract equals the spot price of a bond that matures in nine years and eleven months: $F_{t+1}^0 = S_{t+1}^{119} = \frac{1}{(1+y_{t+1}^{119})^{119}}$, where y_{t+1}^{119} is found by linear interpolation. Similarly, at $t+1$ the price of the six month futures contract equals: $F_{t+1}^5 = S_{t+1}^{119}(1 + y_{t+1}^5)^5$, where y_t^5 is found by linear interpolation.

As in the case of stock indexes, we calculate returns from these prices in foreign

[1]We find virtually identical basis-momentum effects when we incorporate the exchange rate component in returns.

[2]http://econ.jhu.edu/directory/jonathan-wright/.

currency, e.g., $R^1_{bond,p,t+1} = \frac{S^{119}_{t+1}}{F^1_t} - 1$. Using these returns, we calculate basis-momentum and momentum for each contract. We define the basis as the negative of the measure of carry in Koijen et al. (2017). For our sort, we use all months with at least eight bond futures returns available, which leaves us with a final sample of 220 months starting in February 1991. We only report nearby returns for these sorts to be conservative. Synthetic returns of the one month futures contract are highly correlated to first-nearby traded bond futures returns available in Bloomberg. For the shorter time series and smaller cross section of traded returns, we find a High-Low basis-momentum effect that equals 0.38 in Sharpe ratio, which is close to the Sharpe ratio of 0.52 that we report in Table VI. Farther-from-expiring bond futures are typically illiquid and we find that the spreading return between the one- and six-month futures contract is correlated only weakly with the spreading return between the first-nearby and second-nearby futures return in Bloomberg. Having said that, the Sharpe ratio in spreading returns for the sort on basis-momentum is about twice what we find in nearby returns. As in Koijen et al. (2017), we also find a considerably larger spreading effect for the sort on basis.

B Supplementary figures and tables

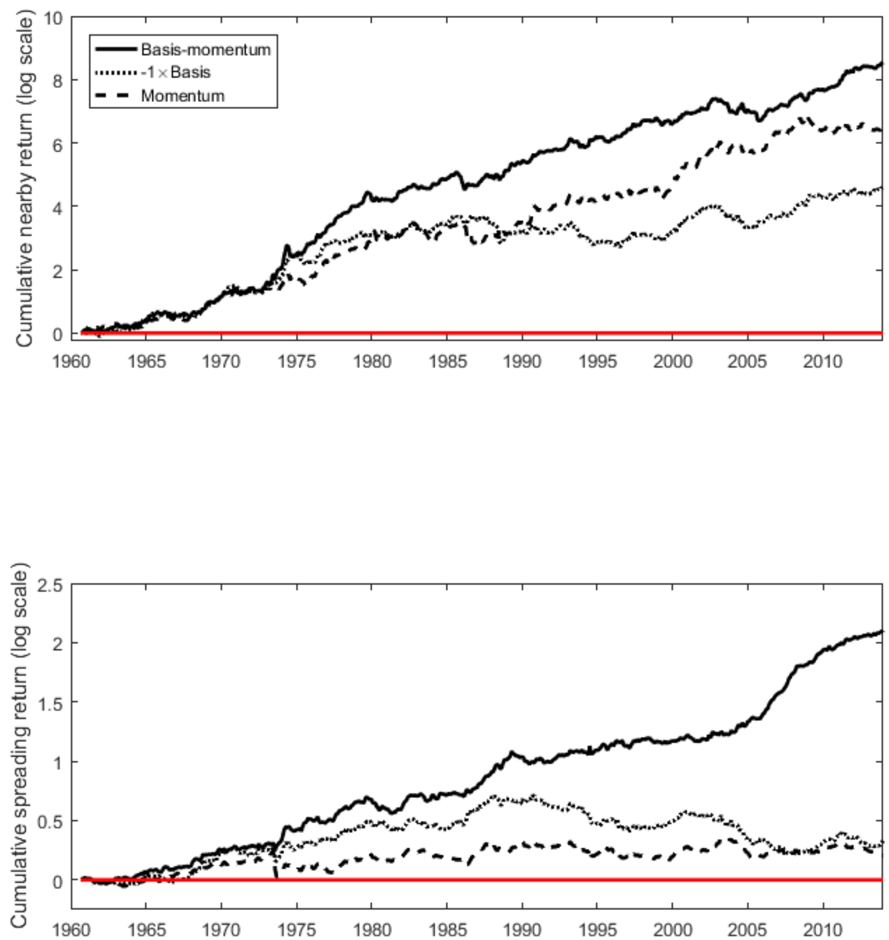

Figure IA.1: Cumulative returns on basis-momentum, basis, and momentum strategies
This figure presents cumulative nearby (top) and spreading (bottom) returns on a log scale for the High4-minus-low4 basis-momentum, basis, and momentum portfolios. The High4 and Low4 portfolios, respectively, contain the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

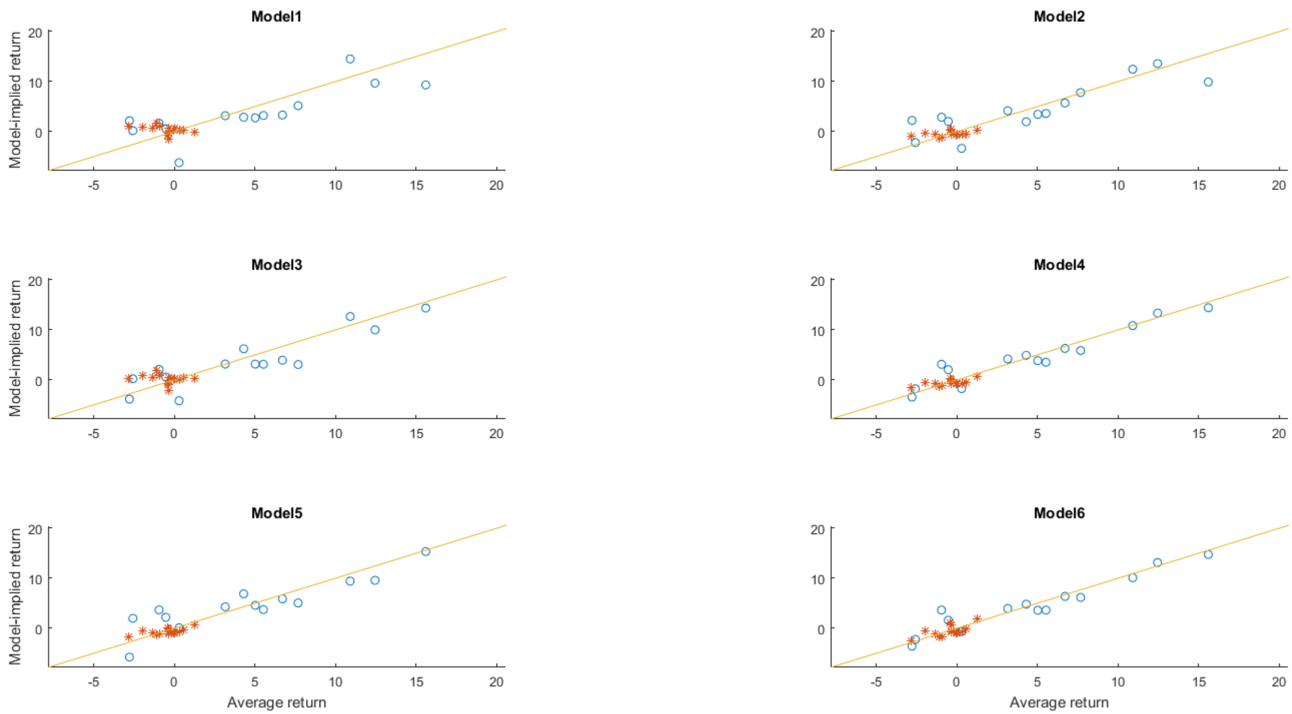

Figure IA.2: Model-implied expected returns versus historical average returns
This figure presents scatter plots of model-implied expected returns versus historical average returns. The model-implied returns are calculated using the six models analyzed in Table IV. The test assets are nearby returns (circles) and spreading returns (crosses) of portfolios sorted on basis-momentum, basis, momentum, and sector. The sample period is August 1960 through February 2014.

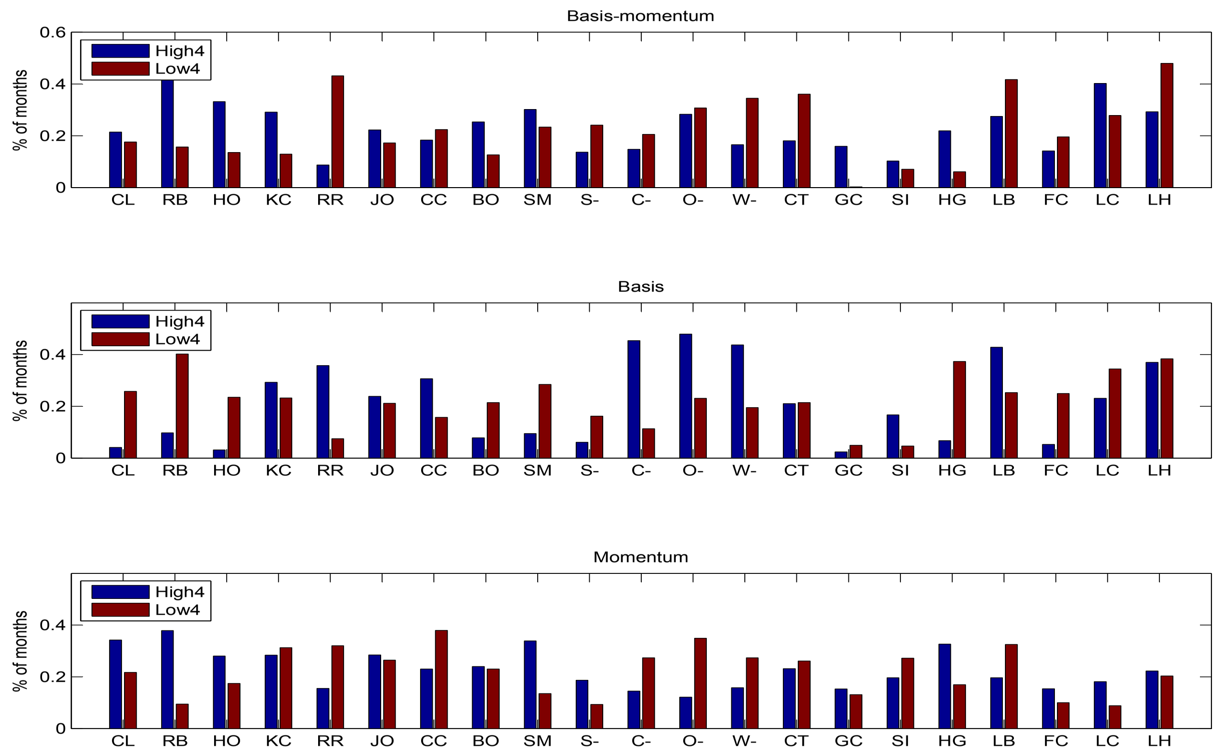

Figure IA.3: Composition of High4 and Low4 portfolios in commodity sorts
This figure presents the fraction of months in which a given commodity (see symbols in Table IA.I) is either among the top four (blue) or bottom four (red) commodities ranked on the three signals of interest: basis-momentum, basis, and momentum. The percentages are calculated as a fraction of the total number of months in which a given commodity is included in the sample. The sample period is August 1960 through February 2014.

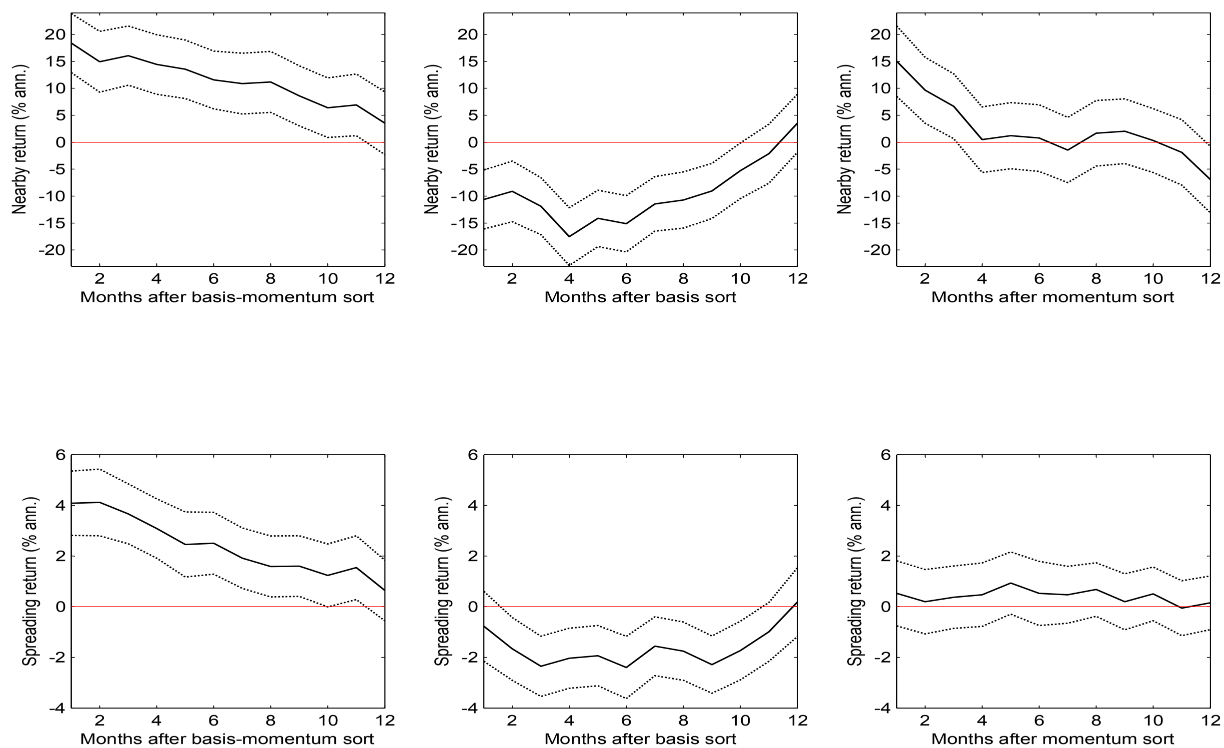

Figure IA.4: Nearby and spreading returns up to one year after portfolio formation
This figure presents average nearby (top) and spreading (bottom) returns (in annualized %) for the High4-minus-Low4 basis-momentum, basis, and momentum portfolios up to one year after portfolio formation. That is, with the sort performed at the end of month t, we present average returns (plus and minus two standard errors) for months $t + 1, ..., t + 12$. The sample period is August 1960 through February 2014.

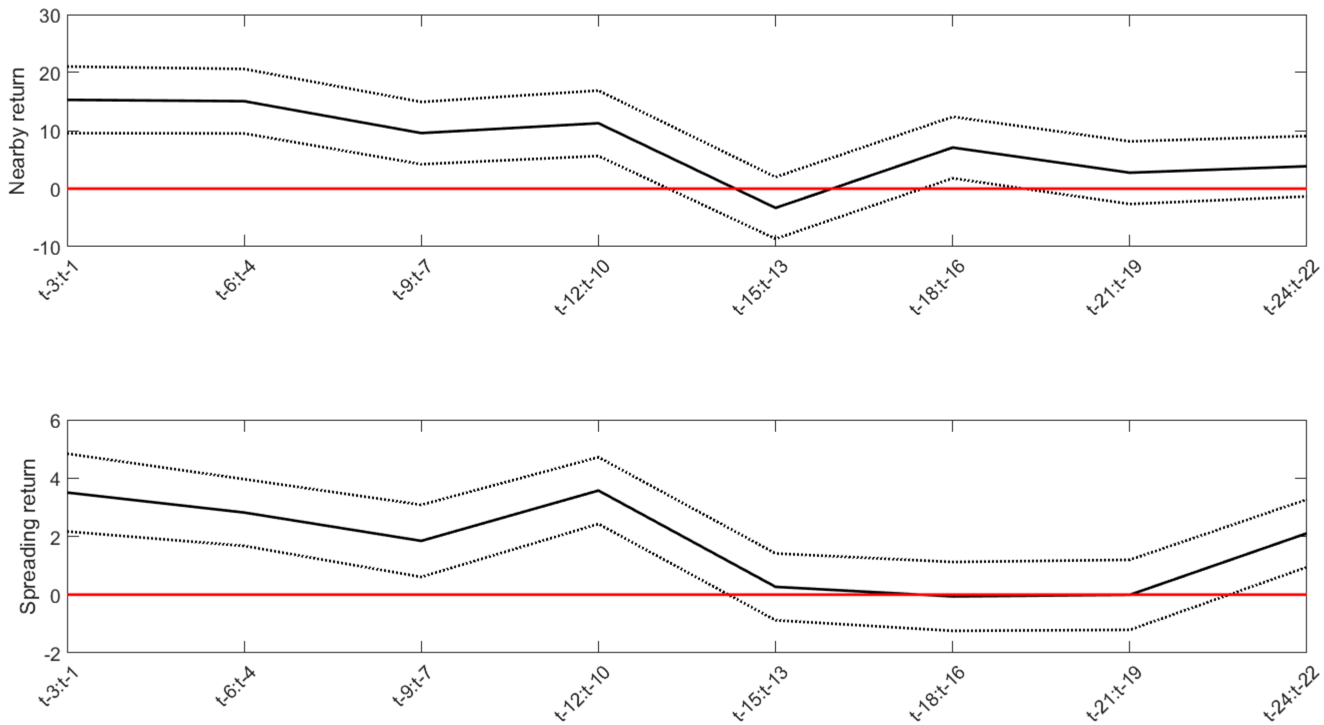

Figure IA.5: Basis-momentum returns over various ranking periods
This figure presents average nearby (top) and spreading (bottom) returns (in annualized %, plus and minus two standard errors) for alternative High4-minus-Low4 basis-momentum portfolios that rank 21 commodities on basis-momentum calculated using quarterly first-nearby and second-nearby returns. There are a total of eight quarterly ranking periods from two years to one-month before portfolio formation. The sample period is August 1960 through February 2014.

Table IA.I: Overview of commodity futures contracts
This table presents the sample of first- and second-nearby futures returns ($R^{T_1}_{fut,i,t+1}$ and $R^{T_2}_{fut,i,t+1}$) for 32 commodities. The table lists for each commodity: sector, symbol, whether it belongs to the smaller sample of Szymanowska et al. (2014), the first observation of a return on the second-nearby contract, as well as average return and standard deviation for both contracts.

Name	Sector	Mnemonic	In small sample?	First obs.	$R^{T_1}_{fut,i,t+1}$ Avg. ret.	$R^{T_1}_{fut,i,t+1}$ St. dev.	$R^{T_2}_{fut,i,t+1}$ Avg. ret.	$R^{T_2}_{fut,i,t+1}$ St. dev.
Crude Oil	Energy	CL	Y	198304	11.68	32.83	11.99	30.77
Gasoline	Energy	HU/RB	Y	198501	18.18	34.57	16.03	31.28
Heating Oil	Energy	HO	Y	197904	9.63	30.98	8.61	29.38
Natural Gas	Energy	NG	N	199005	-5.18	49.62	-0.20	42.44
Gas-Oil-Petroleum	Energy	LF	N	198909	13.35	30.69	12.53	29.02
Propane	Energy	PN	N	198710	23.38	46.89	20.41	39.31
Rough Rice	Grains	RR	Y	198609	-3.54	27.68	1.20	26.04
Sugar	Grains	SB	N	196102	6.54	42.82	8.02	39.01
Corn	Grains	C-	Y	195908	-1.28	23.92	0.07	23.05
Oats	Grains	O-	Y	195908	0.24	29.28	0.28	26.91
Wheat	Grains	W-	Y	195908	-0.87	24.80	0.80	23.90
Canola	Grains	WC	N	197702	-0.38	21.99	0.87	20.58
Barley	Grains	WA	N	198906	-1.16	22.01	1.78	22.05
Cotton	Ind. Mat.	CT	Y	195908	2.40	23.68	3.96	22.10
Lumber	Ind. Mat.	LB	Y	196911	-4.11	27.37	-1.72	23.27
Rubber	Ind. Mat.	YR	N	199202	4.61	32.74	3.45	31.48
Feeder Cattle	Meats	FC	Y	197112	3.69	16.24	5.35	15.58
Live Cattle	Meats	LC	Y	196412	5.02	16.21	4.66	14.19
Lean Hogs	Meats	LH	Y	196603	4.36	25.13	7.74	22.53
Pork Bellies	Meats	PB	N	196204	2.88	33.27	4.78	30.91
Gold	Metals	GC	Y	197501	1.50	19.58	1.45	19.63
Silver	Metals	SI	Y	196307	4.26	31.35	4.47	31.32
Copper	Metals	HG	Y	195908	11.66	26.79	10.61	25.36
Palladium	Metals	PA	N	197702	12.08	35.12	13.04	33.70
Platinum	Metals	PL	N	196902	5.22	27.56	5.12	27.66
Soybean Oil	Oilseeds	BO	Y	195908	6.65	29.33	6.14	28.05
Soybean Meal	Oilseeds	SM	Y	195908	9.91	29.02	10.24	28.03
Soybeans	Oilseeds	S-	Y	195908	6.04	25.86	7.36	25.60
Coffee	Softs	KC	Y	197209	6.68	37.68	5.17	35.47
Orange Juice	Softs	JO	Y	196703	5.53	32.79	5.28	31.54
Cocoa	Softs	CC	Y	195908	3.40	30.86	3.23	29.28
Milk	Softs	DE	N	199602	5.67	23.91	6.08	18.02

Table IA.II: 32 Commodities sorted on basis-momentum

This table is similar to Table I in the paper, but uses the larger cross-section of 32 commodities. We present average nearby (Panel A) and spreading (Panel B) returns of portfolios sorted on basis-momentum, basis, and momentum. The High4 and Low4 portfolio contain the top and bottom four ranked commodities, respectively, whereas the Mid portfolio contains all remaining commodities (which number is time-varying). In each post-ranking month $t+1$, the portfolio's nearby return is the equal-weighted average return of first-nearby contracts ($R^{nb}_{p,t+1} = R^{T_1}_{p,t+1}$), whereas the spreading return is the equal-weighted average of the difference between the return of the first-nearby and second-nearby contract ($R^{spr}_{p,t+1} = R^{T_1}_{p,t+1} - R^{T_2}_{p,t+1}$). 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 ($R^{nb}_{p,t+1}$)						
Avg. ret.	20.46	4.12	-1.63	22.09	-7.68	18.65
(t)	(7.42)	(2.12)	(-0.63)	(6.98)	(-2.52)	(5.01)
Sharpe	1.01	0.29	-0.09	0.95	-0.34	0.68
Panel B: Spreading returns ($R^{spr}_{p,t+1}$)						
Avg. ret.	1.71	-0.22	-3.33	5.04	-0.55	0.03
(t)	(2.80)	(-1.05)	(-6.57)	(6.40)	(-0.66)	(0.03)
Sharpe	0.38	-0.14	-0.90	0.87	-0.09	0.00

Table IA.III: Basis-momentum returns in subperiods

This table presents average nearby and spreading returns in subperiods of about ten years for the High4-minus-Low4 portfolio sorted on basis-momentum, basis, and momentum.

	Basis-momentum		Basis		Momentum	
	$R^{nb}_{p,t+1}$	$R^{spr}_{p,t+1}$	$R^{nb}_{p,t+1}$	$R^{spr}_{p,t+1}$	$R^{nb}_{p,t+1}$	$R^{spr}_{p,t+1}$
1960-08 to 1969	12.75	2.65	-12.74	-2.26	13.19	1.40
1970 to 1979	33.92	4.42	-22.16	-2.89	22.13	1.01
1980 to 1989	14.09	3.76	-4.32	-2.18	8.76	1.28
1990 to 1999	13.66	1.49	-1.70	1.77	14.58	-1.16
2000 to 2007	12.84	7.23	-9.85	3.24	25.57	0.25
2008 to 2014-02	23.58	6.37	-14.29	-2.12	3.49	0.31

Table IA.IV: Pooled regressions of commodity-level returns on basis-momentum (32 commodities)

This table is similar to Table II in the paper and present results from pooled regressions of nearby and spreading returns of 32 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) has 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. Model (8) includes basis-momentum and month×sector fixed effects, which specification we only test post-1986. We present the estimated coefficients on the characteristics (λ's) as well as the R^2. t-statistics are presented underneath each estimate and are calculated using standard errors clustered in the time dimension. Panel C presents results for two decompositions of basis-momentum. In the left block of results, we regress futures returns on momentum and second-nearby momentum ($M^{T_2}_{i,t}$). In the right block of results we regress futures returns on curvature and change in slope (see Section I.B). We present results for the full sample period from August 1960 through February 2014 as well as two sample halves split at January 1986 in the case of Model (7).

	Full sample							Pre-1986	Post-1986	Post-1986
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(7a)	(7b)	(8)
Panel A: Nearby returns ($R^{nb}_{fut,i,t+1}$)										
λ_{BM}	9.69	9.01	9.36	8.50			8.06	10.92	6.59	6.77
(t)	(7.40)	(7.33)	(6.94)	(6.84)			(6.02)	(4.88)	(3.98)	(4.37)
λ_B					-5.47		2.34	3.89	2.58	
(t)					(-2.14)		(0.85)	(0.75)	(0.80)	
λ_M						1.13	0.46	0.52	0.22	
(t)						(2.86)	(1.05)	(0.78)	(0.38)	
Time FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No
Commodity FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Time×Sector FE	No	No	No	No	No	No	No	No	No	Yes
R^2	0.01	0.17	0.01	0.17	0.17	0.17	0.17	0.21	0.15	0.41
Panel B: Spreading returns ($R^{spr}_{fut,i,t+1}$)										
λ_{BM}	1.86	1.63	1.66	1.38			2.03	1.23	2.24	1.70
(t)	(6.53)	(5.72)	(5.71)	(4.73)			(7.02)	(3.03)	(5.73)	(3.69)
λ_B					0.49		0.98	0.55	1.41	
(t)					(0.57)		(1.13)	(0.39)	(1.27)	
λ_M						-0.14	-0.30	-0.18	-0.39	
(t)						(-1.46)	(-2.88)	(-1.15)	(-2.93)	
Time FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No
Commodity FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Time×Sector FE	No	No	No	No	No	No	No	No	No	Yes
R^2	0.01	0.02	0.01	0.02	0.02	0.02	0.03	0.02	0.03	0.11

Panel C: Decomposing basis-momentum predictability

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

Table IA.V: Spanning and GRS tests for alternative basis-momentum factors This table is similar to Panel B of Table III of the paper, but uses alternative definitions of the factors. In Panel A, we define the basis-momentum factors (as well as the basis and momentum factors of the benchmark models of Szymanowska et al. (2014) and Bakshi, Gao and Rossi (2017)) as the High4-minus-Low4 portfolio from a sort that uses the larger set of 32 commodities. In Panel B, we define the commodity factors as the High-minus-Low portfolio from a sort that splits the sample of 21 commodities into two portfolios at the median of each characteristic. The spanning tests ask whether the basis-momentum factors provide an alpha over these two benchmark 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: High4-minus-Low4 factors using 32 commodities

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

	α	(t_α)	β_B^{nb}	$\beta_{B,High4}^{spr}$	$\beta_{B,Low4}^{spr}$	R^2		
R_{BM}^{nb}	18.44	(6.35)	-0.42***	-0.23	-0.11	0.17	GRS-F	25.80
R_{BM}^{spr}	4.53	(6.13)	-0.01	-0.48***	0.30***	0.16	p-val	1.69×10^{-11}

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

	α	(t_α)	β_B^{nb}	β_{AVG}^{nb}	β_M^{nb}	R^2		
R_{BM}^{nb}	16.11	(5.88)	-0.34***	-0.06	0.20***	0.21	GRS-F	23.52
R_{BM}^{spr}	4.27	(5.79)	-0.06***	-0.01	0.02**	0.07	p-val	1.40×10^{-10}

Panel B: Above-minus-below median factors using 21 commodities

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

	α	(t_α)	β_B^{nb}	$\beta_{B,High4}^{spr}$	$\beta_{B,Low4}^{spr}$	R^2		
R_{BM}^{nb}	10.76	(6.11)	-0.37***	-0.61	0.25	0.15	GRS-F	30.83
R_{BM}^{spr}	2.48	(7.18)	-0.01	-0.42***	0.38***	0.17	p-val	1.65×10^{-13}

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

	α	(t_α)	β_B^{nb}	β_{AVG}^{nb}	β_M^{nb}	R^2		
R_{BM}^{nb}	10.18	(5.74)	-0.38***	0.06	0.08	0.15	GRS-F	25.83
R_{BM}^{spr}	2.39	(6.46)	-0.05***	0.01	0.01	0.05	p-val	1.64×10^{-11}

Table IA.VI: Spanning tests for basis and momentum factors
This table presents spanning regressions for the commodity factors of Szymanowska et al. (2014) and Bakshi, Gao and Rossi (2017). Panel A runs regressions of three basis factors (R^{nb}_{B}, $R^{spr}_{B,High4}$, and $R^{spr}_{B,Low4}$) on a two- and four-factor model of the remaining factors. Panel B runs regressions for the average and momentum nearby factors (R^{nb}_{AVG}, and R^{nb}_{M}) on a five-factor model containing all remaining factors. 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: Basis factors

Two-factor model

	α	(t_α)	β^{nb}_{BM}	β^{nb}_{AVG}	R^2		
R^{nb}_{B}	-2.48	(-0.91)	-0.42***	-0.07	0.18	GRS-F	2.98
$R^{spr}_{B,High4}$	-0.79	(-2.25)	-0.03***	0.03***	0.06	p-val	0.031
$R^{spr}_{B,Low4}$	-1.08	(-1.87)	0.04***	0.00	0.03		

Four-factor model

	α	(t_α)	β^{nb}_{BM}	β^{nb}_{AVG}	β^{nb}_{M}	β^{spr}_{BM}	R^2		
R^{nb}_{B}	-0.07	(-0.03)	-0.32***	-0.03	-0.23***	-0.22	0.25	GRS-F	3.17
$R^{spr}_{B,High4}$	-0.43	(-1.25)	-0.01	0.03***	-0.01**	-0.14***	0.12	p-val	0.024
$R^{spr}_{B,Low4}$	-1.75	(-2.90)	0.00	0.00	0.01	0.28***	0.10		

Panel B: Momentum and average factors

	α	(t_α)	β^{nb}_{BM}	β^{nb}_{B}	β^{spr}_{BM}	$\beta^{spr}_{B,High4}$	$\beta^{spr}_{B,Low4}$	R^2		
R^{nb}_{AVG}	4.71	(2.57)	0.01	-0.09**	0.07	1.05***	-0.14	0.03	GRS-F	5.14
R^{nb}_{M}	7.48	(2.24)	0.14*	-0.40***	0.20	0.09	-0.18	0.15	p-val	0.006

Table IA.VII: Cross-sectional asset pricing tests for alternative factors and test assets

This table is similar to Table IV in the paper, but uses the larger set of 32 commodities to construct the factors and the test assets for the portfolio-level test in Panel A as well as the commodity-level test in Panel B. In Panel C, we use the same sample of test portfolios used in Table IV of the paper (based on 21 commodities), but define the factors as the High-minus-Low portfolio from a sort that splits the sample at the median of each characteristic. We test 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 Low4 basis portfolio ($R_{B,High4}^{spr}$ and $R_{B,Low4}^{spr}$). The second model of Bakshi, Gao and Rossi (2017) contains three nearby factors: a market index ("the average factor", R_{AVG}^{nb}), a basis factor (R_B^{nb}), and a momentum factor (R_M^{nb}). The third and fourth model 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 factor to this specification (R_M^{nb} and R_{BM}^{spr}). The portfolio-level test in Panel A and C regress the average returns of 32 commodity-sorted portfolios on their full sample exposures. The portfolios include the nearby and spreading return of 9 portfolios sorted on basis-momentum, basis, and momentum (the High4, Mid, and Low4 portfolio from each of these sorts) and 7 sector portfolios (Energy, Grains, Industrial Materials, Meats, Metals, Oilseeds, and Softs). The commodity-level test in Panel B conducts monthly Fama and MacBeth (1973) cross-sectional regressions of the nearby and spreading returns of 32 commodities on their historical exposure, estimated over a one year rolling window of daily returns. Due to the staggered introduction of commodities in the sample, the size of the cross-section is 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 Kan, Robotti and Shanken (2013) (in angle brackets) in Panels A and C 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 in the $MAPE$ among nearby returns and spreading returns. These measures follow from a regression of average returns on full sample betas in Panels A and C and average returns on average betas in Panel B. We present results for the full sample period from August 1960 through February 2014.

Table IA.VII continued

	γ_0	γ^{nb}_{BM}	γ^{nb}_{B}	γ^{nb}_{AVG}	γ^{nb}_{M}	γ^{spr}_{BM}	$\gamma^{spr}_{B,High4}$	$\gamma^{spr}_{B,Low4}$	R^2 $MAPE$	$MAPE^{nb}$ $MAPE^{spr}$
Panel A: Portfolio-level test with full sample betas (32 commodities)										
Model 1	1.42		-20.25				2.79	-3.58	0.46	[3.92]
	<1.24>		<-4.21>				<2.54>	<-1.88>	[3.09]	[2.25]
Model 2	-0.73		-13.18	5.91	21.22				0.78	[2.41]
	<-2.73>		<-2.38>	<2.28>	<3.75>				[1.62]	[0.83]
Model 3	1.33	23.02	-13.37				2.60	-3.30	0.64	[3.40]
	<1.19>	<3.93>	<-2.08>				<2.09>	<-1.61>	[2.71]	[2.03]
Model 4	-0.84	21.50	-9.03	5.94	19.11				0.92	[1.58]
	<-3.18>	<4.70>	<0.43>	<2.45>	<2.43>				[1.14]	[0.70]
Model 5	-0.99	24.05		6.30					0.88	[2.03]
	<-3.62>	<6.51>		<3.00>					[1.35]	[0.66]
Model 6	-0.90	20.95		6.01	18.48	4.87			0.93	[1.55]
	<-3.27>	<1.84>		<2.55>	<2.23>	<1.27>			[1.15]	[0.74]
Panel B: Commodity-level test with rolling one-year betas (32 commodities)										
Model 1	1.72		-11.89				1.39	1.94	0.49	[3.69]
	(2.19)		(-2.68)				(1.05)	(1.08)	[2.86]	[2.03]
Model 2	-0.03		-17.13	4.87	-4.41				0.77	[2.78]
	(-0.08)		(-3.64)	(2.60)	(-0.85)				[1.98]	[1.18]
Model 3	1.34	13.79	-12.47				1.42	2.06	0.53	[3.54]
	(1.86)	(3.13)	(-2.70)				(1.12)	(1.21)	[2.73]	[1.93]
Model 4	-0.07	14.75	-13.36	4.92	-2.46				0.77	[2.71]
	(-0.18)	(3.33)	(-2.73)	(2.64)	(-0.45)				[1.96]	[1.21]
Model 5	0.18	12.44		4.47					0.63	[3.68]
	(0.41)	(2.91)		(2.36)					[2.42]	[1.17]
Model 6	0.05	14.55		4.68	-1.14	0.97			0.78	[2.75]
	(0.13)	(3.34)		(2.51)	(-0.23)	(0.64)			[1.88]	[1.02]
Panel C: Portfolio-level test using above-minus-below median factors (21 commodities)										
Model 1	-0.35		-18.47				1.72	0.19	0.65	[3.05]
	<-0.30>		<-4.05>				<2.44>	<-1.10>	[2.23]	[1.41]
Model 2	-0.79		-12.49	5.49	9.45				0.82	[2.22]
	<-3.03>		<-3.73>	<2.46>	<1.44>				[1.48]	[0.74]
Model 3	-0.63	16.87	-13.45				1.50	0.10	0.80	[2.31]
	<-0.65>	<2.80>	<-2.06>				<1.88>	<-1.05>	[1.72]	[1.13]
Model 4	-0.82	14.38	-8.41	5.40	9.58				0.91	[1.49]
	<-2.92>	<2.81>	<-0.60>	<1.79>	<1.76>				[1.09]	[0.69]
Model 5	-0.88	18.16		5.57					0.84	[2.17]
	<-3.02>	<5.46>		<1.94>					[1.41]	[0.65]
Model 6	-0.91	14.23		5.44	10.04	2.63			0.91	[1.39]
	<-2.90>	<1.32>		<1.79>	<2.32>	<0.93>			[1.05]	[0.72]

Table IA.VIII: Double sorts: Basis-momentum versus positions of traders
This table presents average nearby (Panel A) and spreading (Panel B) returns when we 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 using twelve-month average hedging pressure (HP) as well as three-month average spreading pressure (SP). To be precise, we allocate a commodity to the High (Low) control group, in months where HP or SP is above (below) the median for a given commodity. 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. For the case of spreading pressure, we present in the last row of each panel the diff-in-diff in the basis-momentum effect among commodities with high versus low spreading pressure. In each post-ranking month $t+1$, the portfolio's nearby return is the equal-weighted average return of first-nearby contracts, whereas the spreading return is the equal-weighted average of the difference between the return of the first-nearby and second-nearby contract. The sample period is from February 1986 to February 2014, dictated by availability of CFTC position data.

		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 ($R^{nb}_{p,t+1}$)									
Basis-momentum	High	10.44	(3.66)						
	Low	-2.79	(-1.14)						
	Diff	13.23	(5.24)						
Hedging pressure	High	6.29	(2.43)	13.82	(4.27)	-0.98	(-0.33)	14.80	(4.50)
	Low	0.60	(0.22)	6.21	(1.63)	-5.58	(-1.74)	11.78	(3.05)
	Diff	5.68	(2.25)	7.61	(2.13)	4.59	(1.37)		
Spreading pressure	High	-3.92	(-1.26)	7.61	(1.72)	-9.09	(-2.59)	16.70	(3.65)
	Low	6.27	(2.09)	7.55	(2.09)	-0.67	(-0.16)	8.22	(1.90)
	Diff	-10.19	(-3.23)	0.06	(0.01)	-8.42	(-1.89)		
							Diff-in-Diff	8.47	(1.42)
Panel B: Spreading returns ($R^{spr}_{p,t+1}$)									
Basis-momentum	High	0.11	(0.32)						
	Low	-2.53	(-7.31)						
	Diff	2.64	(5.77)						
Hedging pressure	High	-1.40	(-3.81)	0.46	(0.87)	-3.20	(-6.19)	3.66	(5.13)
	Low	-1.25	(-3.60)	0.16	(0.32)	-2.03	(-4.01)	2.19	(3.20)
	Diff	-0.15	(-0.32)	0.30	(0.41)	-1.17	(-1.72)		
Spreading pressure	High	-2.05	(-4.30)	0.30	(0.42)	-3.06	(-4.74)	3.37	(3.63)
	Low	-0.76	(-1.91)	-0.41	(-0.79)	-1.11	(-1.62)	0.70	(0.85)
	Diff	-1.29	(-2.27)	0.71	(0.85)	-1.96	(-2.14)		
							Diff-in-Diff	2.67	(2.15)

Table IA.IX: Does volatility predict basis-momentum? OLS estimation
This table is similar to Table VIII in the paper, but estimates the predictive regressions of basis-momentum returns on lagged volatility using OLS. Standard errors are Newey-West with lag length k. The sample period is August 1960 through February 2014.

	Basis-momentum						Basis	Momentum
k	1				6	12	12	12
	High4	Mid	Low4	H4-L4	H4-L4	H4-L4	H4-L4	H4-L4
				Nearby returns ($R^{nb}_{p,t+1:t+k}$)				
v_1^{mkt}	2.25	-1.02	-5.31	7.56	7.25	5.78	-3.84	-4.11
(t)	(0.52)	(-0.27)	(-1.42)	(1.85)	(2.13)	(1.91)	(-0.95)	(-2.47)
R^2	0.00	0.00	0.01	0.01	0.05	0.05	0.02	0.03
v_1^{avg}	2.05	-2.03	-5.04	7.09	5.64	4.60	-2.12	-3.24
(t)	(0.60)	(-0.66)	(-1.39)	(1.94)	(1.81)	(1.59)	(-0.55)	(-1.63)
R^2	0.00	0.00	0.01	0.01	0.03	0.03	0.00	0.02
				Spreading returns ($R^{spr}_{p,t+1:t+k}$)				
v_1^{mkt}	-0.39	-0.41	-1.24	0.85	1.20	1.27	-0.81	-0.08
(t)	(-0.86)	(-1.16)	(-2.73)	(1.16)	(1.74)	(3.02)	(-1.59)	(-0.29)
R^2	0.00	0.00	0.01	0.00	0.02	0.04	0.02	0.00
v_1^{avg}	-0.66	-0.37	-1.58	0.92	1.37	1.53	-0.23	-0.07
(t)	(-1.32)	(-0.99)	(-3.89)	(1.33)	(2.18)	(3.59)	(-0.34)	(-0.19)
R^2	0.00	0.00	0.02	0.00	0.03	0.07	0.00	0.00

Table IA.X: Double sorts: Basis-momentum versus Amihud illiquidity
This table presents average nearby (Panel A) and spreading (Panel B) returns when we sort commodities into four portfolios (with t-statistics in parentheses). These portfolios are at the intersection of an independent sort into two basis-momentum groups (split at the median) and two groups sorted on Amihud illiquidity (split at the median). Amihud illiquidity is calculated for each commodity futures contract as an annual average of daily returns over dollar volume ($R^{T_n}_{fut,i,d}/Vol^{T_n}_{i,d}$). We average the Amihud measure for the first- and second-nearby contract ($n = 1, 2$), to ensure we are not focusing on the most liquid first-nearby contract alone. The first two columns present the single sort on the Amihud measure. The last six columns present the double sort, with the last two columns containing the High-Low basis-momentum return in each control group. We present in the last row of each panel the diff-in-diff in the basis-momentum effect among illiquid versus liquid commodities. In each post-ranking month $t + 1$, the portfolio's nearby return is the equal-weighted average return of first-nearby contracts, whereas the spreading return is the equal-weighted average of the difference between the return of the first-nearby and second-nearby contract. We present results for the full sample period (using only those months where we have at least 8 commodities with available data).

		Single sort on row variable		Double sort on row variable and basis-momentum					
				Basis-momentum					
		Avg. ret.	(t)	High	(t)	Low	(t)	High-Low	(t)
Panel A: Nearby returns ($R^{nb}_{p,t+1}$)									
Amihud	Illiquid	5.76	(2.51)	17.58	(5.18)	-4.62	(-1.70)	22.21	(6.21)
	Liquid	4.26	(1.75)	11.18	(3.90)	-1.81	(-0.69)	13.00	(4.80)
	Diff	1.51	(0.83)	6.40	(2.12)	-2.81	(-1.09)		
							Diff-in-Diff	9.21	(2.25)
Panel B: Spreading returns ($R^{spr}_{p,t+1}$)									
Amihud	Illiquid	-0.46	(-1.40)	1.39	(2.52)	-2.21	(-5.15)	3.60	(5.18)
	Liquid	-0.79	(-2.68)	0.30	(0.66)	-1.85	(-5.37)	2.15	(4.01)
	Diff	0.33	(0.87)	1.09	(1.66)	-0.36	(-0.72)		
							Diff-in-Diff	1.45	(1.72)

Table IA.XI: Basis-momentum across the futures curve

This table presents the unconditional performance of commodity-portfolios sorted on alternative measures of basis-momentum. We present the performance of High4-minus-Low4 portfolios in second- and third-nearby futures returns ($R^{T_2}_{p,t+1}$ and $R^{T_3}_{p,t+1}$) as well as spreading returns between the second- and third-nearby and the third- and fourth-nearby contracts ($R^{T_2}_{p,t+1} - R^{T_3}_{p,t+1}$ and $R^{T_3}_{p,t+1} - R^{T_4}_{p,t+1}$). In the first block of results, commodities are sorted on our usual measure of basis-momentum, BM_t. The next two blocks of results sort commodities on basis-momentum measured using farther-from-expiring contracts, denoted $BM^{2,3}_t$ and $BM^{3,4}_t$, respectively. For these sorts, we also present performance statistics using only those months when less than or equal to three out of eight commodities in the High4 and Low4 portfolios overlap between BM_t and one of the two alternative measures (denoted, for example, $BM^{2,3}_t|BM_t$). The sample period is from August 1960 through February 2014.

Sorting variable	Average returns for High4-Low4 portfolio	$R^{T_2}_{p,t+1}$	$R^{T_2}_{p,t+1} - R^{T_3}_{p,t+1}$	$R^{T_3}_{p,t+1}$	$R^{T_3}_{p,t+1} - R^{T_4}_{p,t+1}$
BM_t	Avg. ret.	14.55	2.31	12.42	0.98
	(t)	(5.88)	(4.57)	(5.35)	(2.06)
	Sharpe	0.80	0.63	0.73	0.32
$BM^{2,3}_t$	Avg. ret.	16.46	2.52		
	(t)	(6.75)	(5.00)		
	Sharpe	0.92	0.68		
$BM^{2,3}_t \vert BM_t$	Avg. ret.	7.43	1.58		
(231 Months)	(t)	(1.85)	(1.94)		
	Sharpe	0.42	0.44		
$BM^{3,4}_t$	Avg. ret.			11.96	0.91
	(t)			(4.85)	(1.89)
	Sharpe			0.71	0.28
$BM^{3,4}_t \vert BM_t$	Avg. ret.			11.52	0.57
(361 Months)	(t)			(3.69)	(0.97)
	Sharpe			0.67	0.18

Table IA.XII: Stability of basis-momentum portfolio
This table analyzes the stability of the basis-momentum (as well as basis and momentum) portfolios. We ask how many of the four commodities in the High4 and Low4 portfolio stay in that portfolio in a given sample month. Similarly, we ask how many commodities stay in a portfolio without requiring the investor to roll into a new contract. We present results for the full sample period from August 1960 through February 2014.

	# of commodities (out of four)			
	Stay		Stay without roll	
	High4	Low4	High4	Low4
Basis-momentum	3.24	3.26	1.38	1.54
Basis	2.72	2.67	1.37	1.02
Momentum	3.17	3.17	1.34	1.56

Table IA.XIII: Varying the number of commodities in extreme portfolios
This table is similar to Table I in the paper, but varies the number of commodities (#) in the High and Low basis-momentum portfolio from one to eight. We present average nearby and spreading returns. For each sort, we present results for sample months that contain at least as many commodities as are allocated to the High and Low portfolio.

	Nearby returns ($R^{nb}_{BM,H4-L4,t+1}$)			Spreading returns ($R^{spr}_{BM,H4-L4,t+1}$)		
#	Avg. ret.	(t)	Sharpe	Avg. ret.	(t)	Sharpe
1	29.39	(5.34)	0.73	5.46	(3.62)	0.50
2	24.70	(6.40)	0.87	5.02	(5.06)	0.69
3	20.02	(6.63)	0.91	4.51	(5.81)	0.79
4	18.38	(6.73)	0.92	4.08	(6.43)	0.88
5	18.22	(6.86)	0.97	4.17	(7.25)	1.03
6	18.39	(7.24)	1.06	4.24	(8.17)	1.19
7	15.21	(6.05)	0.94	3.67	(7.32)	1.14
8	15.30	(6.32)	1.02	3.43	(7.31)	1.18

Table IA.XIV: Time-series predictability

This table presents results from two tests that analyze whether lagged basis-momentum predicts nearby (left block of results) and spreading (right block of results) returns in the time-series of an individual commodity. In Panel A, we present for each of 21 commodities (symbols are matched to the full names in Table IA.I) average nearby and spreading returns conditioning on the sign of lagged basis-momentum, and we test the difference ($\mu_{diff} = \mu(R_{fut,i,t+1}|BM_{i,t} > 0) - \mu(R_{fut,i,t+1}|BM_{i,t} \leq 0)$). This test is inspired by Moskowitz, Ooi and Pedersen (2012) and is interesting because it does not impose a linear relation between basis-momentum and returns. Next, we present the coefficient (δ_{BM}), t-statistic, and R^2 from a time-series regression of returns on lagged basis-momentum. Panel B counts the number of commodities (out of 21) for which the difference and the coefficient, respectively, are positive or negative. As a benchmark, we also present the counts when using as signal $X_{i,t}$ either basis ($B_{i,t}$) or momentum ($M_{i,t}$). We test significance at the 10%-level using White heteroskedasticity-robust standard errors. Throughout, we use all the returns available for a particular commodity. There is one observation less for the case of basis in Panel B, because gold is always in contango.

Panel A: Futures return on lagged basis-momentum signals

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

Table IA.XIV continued

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

Table IA.XV: Average spot and roll returns in commodity sorts

This table decomposes average first-nearby futures returns in two components: the roll return (coming from rolling over to the second-nearby contract once the first-nearby contract is close to expiration), and the spot return. The roll return equals zero when the strategy does not roll. We sort commodities on basis-momentum, basis, and momentum. In each post-ranking month $t+1$, returns and their components are calculated as equal-weighted averages across the commodities in a portfolio. The sample period is from August 1960 through February 2014.

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

Table IA.XVI: Basis-momentum net of seasonalities
This table presents average nearby and spreading returns from a sort on basis-momentum into three portfolios: High4, Mid, and Low4. For the sort in Panel A, we clean commodity returns from seasonal effects ex ante, by running a regression of returns on twelve monthly dummies. We then use the residuals to calculate the basis-momentum characteristic and the post-ranking portfolio returns. For Panel B, we only clean the basis-momentum characteristic by regressing it on the twelve monthly dummies. We then sort commodities on the residual. We present results for the full sample period.

	High4	Mid	Low4	High4-Low4
Panel A: De-seasonalize returns ex ante				
		Nearby returns		
Avg. ret.	10.41	0.40	-8.58	18.99
(t)	(4.48)	(0.19)	(-3.66)	(7.11)
		Spreading returns		
Avg. ret.	1.75	0.49	-2.23	3.98
(t)	(3.67)	(2.03)	(-5.55)	(6.58)
Panel B: De-seasonalize the basis-momentum characteristic				
		Nearby returns		
Avg. ret.	14.59	4.30	-2.95	17.54
(t)	(6.18)	(2.07)	(-1.23)	(6.45)
		Spreading returns		
Avg. ret.	1.11	-0.07	-2.72	3.83
(t)	(2.29)	(-0.27)	(-6.58)	(6.15)