

# Can commodity futures risk factors predict economic growth?

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## Abstract

This paper examines whether commodity futures risk factors can predict the future economic growth. We consider various risk factors suggested by the literature capturing spot or term premia, and find that after controlling for the effects of traditional predictors, macroeconomic or equity risk factors, only three factors capturing term premia on the basis-momentum, basis, and change in slope remain significant predictors for future economic growth especially in the long horizon. Our findings highlight the importance of the term premia rather than the spot premia. Moreover, the further analyses on the term premia exhibit that the change in slope factor is the strongest and most robust predictor among them, and the improved explanatory power from the model including the term premia on the high- and low-change in slope contracts separately rather than including the term premia on the high-minus-low change in slope contracts. In line with Szymanowska et al. (2014), our results imply the importance of considering the long- and short-legs of the term premia separately in commodity futures markets.

JEL classification: G10; G11; G12

Keywords: Commodity futures; Basis; Momentum; Term premia; Economic growth

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## 1. Introduction

There has been a long debate regarding which factors are priced as risk factors in the commodity futures markets, and the literature has not reached any consensus yet. For example, Miffre and Rallis (2007) employ the returns on government bond index, the S&P 500 composite index, and GSCI (Goldman Sachs Commodity Index) as risk factors. However, Daskalaki et al. (2014) empirically examine existing models that are popular in the finance literature, such as a macro-factor model or an equity-motivated factor model (for example, Fama and French's (1993) three-factor model), in the commodity futures markets and find that risk factors in other asset markets are not priced in the commodity markets, which shows that the commodity markets are segmented from other markets, especially from the equity market.

Recent studies on commodity futures markets suggest new factor models that are unique to commodity futures markets. Szymanowska et al. (2014) (hereafter, SRGN) focus on the basis, the difference between the futures and spot prices, which has long been believed as a predictor of expected futures returns based on traditional theories, such as the theory of storage or the hedging pressure hypothesis. Based on the basis, SRGN construct the mimicking portfolio, which is the long-short portfolio buying high-basis contracts and selling low-basis contracts. More importantly, they consider two types of factors, one constructed by the nearby return on the mimicking portfolio capturing the spot premium (*basis nearby factor*), and the other constructed by the spreading return (difference between the first- and second-nearby returns) on the mimicking portfolio capturing the term premium (*basis spreading factor*). They find that the basis nearby factor successfully explains various spot premia, but to explain term premia, two more factors that are the high-basis spreading factor and the low-basis spreading factor are required. Interestingly, they empirically show that in explaining term premia the long- and short-legs of the basis spreading factors (that are the high-basis spreading factor and the low-basis spreading factor) should be considered separately.

Bakshi et al. (2017) (hereafter, BGR) suggest a three-factor model including an average commodity (nearby) factor, a carry (nearby) factor (or, a basis nearby factor), and a momentum (nearby) factor, and show that their model successfully explains the cross-sectional variation of commodity

returns. More recently, Boons and Prado (2018) (hereafter, BP) suggest a new return predictor, named the basis-momentum, and show that factors based on the basis-momentum – more precisely, the basis-momentum nearby and spreading factors - are significantly priced in the commodity futures markets even after controlling for BGR's and SRGN's factors. BP especially highlight that the basis-momentum is a meaningful predictor as it captures the change in slope and the average curvature of the futures term structure, and conclude that the curvature component seems to be more important than the change in slope.

In this paper, we examine whether the commodity futures risk factors recently documented by SRGN, BGR, and BP, can predict the future Gross Domestic Product (GDP) growth. While recent studies suggest a new return predictor or a new risk factor in the commodity futures markets, there is little evidence of a relation between the commodity futures risk factors and the future economic growth. The purpose of this paper is to fill this gap by exploring the predictability of the newly suggested commodity futures risk factors for future economic growth.

Our motivation is closely related to Liew and Vassalou (2000). According to Merton (1973)'s intertemporal asset pricing model (ICAPM), risk factors other than the market factor should be closely correlated to the state variables that summarize the investment opportunity set investors face. In Merton's sense, a variable can be a risk factor if it can predict the future economic state such as GDP growth. Following this notion, Liew and Vassalou (2000) examine whether three equity risk factors – value, size, and momentum factors – can predict the future GDP growth, and report that value and size factors exhibit the significant predictability for the future GDP growth. Our paper is similar to Liew and Vassalou (2000) in the sense that we examine whether risk factors suggested in the literature predict the future economic growth, but can be distinguished from them and other papers such as Harvey (1989) and Vassalou (2003) as our main focus lies in the risk factors suggested in the commodity futures markets. To the best of our knowledge, no papers have examined the predictability of the commodity risk factors for future economic growth.

The literature on commodity futures markets has reported that the commodity futures factors have quite low relations with other markets' factors. With respect to the commodity futures momentum factors, Miffre and Rallis (2007) and Kang and Kwon (2017) also report that the commodity futures

momentum cannot be fully explained by the bond and equity market factors or equity risk factors. Daskalaki et al. (2014) also document that a macroeconomic factor model and an equity factor model fails to explain commodity futures returns. Our results also show that the correlations between commodity futures risk factors and equity risk factors are less than 10% in absolute value in most of the cases. Moreover, the commodity futures risk factors of our interests, such as the basis or the basis-momentum factors, are unique to commodity futures markets that are related to the term structure of commodity futures.

In this paper, we first compare the predictive power for future economic growth across commodity futures risk factors. Following SRGN, we consider two types of factors, one constructed by the nearby return on the mimicking portfolio capturing the spot premium, and the other constructed by the spreading return (difference between the first- and second-nearby returns) on the mimicking portfolio capturing the term premium. We take account of all factors suggested by SRGN, BGR, and BP. Specifically, the SRGN model includes three factors: (1) the nearby return of the High4-minus-Low4 basis portfolio (basis nearby factor,  $CR^{nb}$ ), (2) the spreading return of the High4 basis portfolio (high-basis spreading factor,  $CR_H^{spr}$ ), and (3) the spreading return of the Low4 basis portfolio (low-basis spreading factor,  $CR_L^{spr}$ ). The BGR model includes three factors: (1) the average nearby return of all sample commodity futures (average factor,  $AVG^{nb}$ ), (2) the nearby return of the High4-minus-Low4 basis portfolio as in SRGN (basis nearby factor,  $CR^{nb}$ ) and (3) the nearby return of the High4-minus-Low4 momentum portfolio (12-month momentum factor  $MOM12^{nb}$  or six-month momentum factor  $MOM6^{nb}$  depending on the ranking period of momentum, which is 12 or 6 months, respectively). The BP model includes two factors: (1) the nearby return of the High4-minus-Low4 basis-momentum portfolio (basis-momentum nearby factor,  $BM^{nb}$ ) and (2) the spreading returns of the High4-minus-Low4 basis-momentum portfolio (basis-momentum spreading factor,  $BM^{spr}$ ). Lastly, we further decompose  $BM^{nb}$  ( $BM^{spr}$ ) into two factors: (1) the nearby (spreading) return of the High4-minus-Low4 change in slope portfolio,  $SL^{nb}$  (slope nearby factor) ( $SL^{spr}$  (slope spreading factor)), (2) the nearby (spreading) return of the High4-minus-Low4 curvature portfolio,  $CV^{nb}$  (curvature nearby factor) ( $CV^{spr}$  (curvature spreading factor)).

Our results show that the average and the basis-momentum nearby factors show significant predictive power for future economic growth within one-year horizon. In the longer horizon from one to two years, the 12-month momentum nearby factor and the basis-momentum and high-basis spreading factors also show significant predictive power for future economic growth. Moreover, when we compare the predictive power of the change in slope with that of the average curvature spreading factors, the change in slope factor appears to be the main driver of the basis-momentum spreading factor's predictability for future economic growth.

Next, we investigate the predictability of commodity futures risk factors for future economic growth after controlling for the traditional economic growth predictors, macroeconomic factors and equity risk factors, to examine whether commodity futures risk factors have economic-growth-related information independent of these traditional predictors. Controlling for traditional predictors affects differently for the predictability of commodity futures risk factors. For example, we find that the predictive power of  $MOM12^{nb}$  is improved if the macroeconomic factors are included, which may indicate that  $MOM12^{nb}$  can jointly play a role as a state variable with the macroeconomic factors, but it becomes insignificant if the equity factors are controlled for. However, we find that two long-term predictors, the basis-momentum spreading factor and the high-basis spreading factor, consistently remain significant after controlling for other predictors. Moreover, between the two components of the basis-momentum spreading factor, we find that the slope spreading factor consistently has the strong and robust predictability for the future GDP growth especially in the long term. Our results exhibit that the predictive power of commodity futures nearby return factors for the future GDP growth is largely subsumed by existing factors, either macroeconomic factors or equity risk factors. Moreover, our results highlight the importance of spreading return factors in the commodity futures markets as a state variable in the context of Merton's ICAPM because they seem to embody an economic source unique to the commodity futures markets and also significantly predict the future economic growth. The most impressive finding is that the slope spreading factor, which is related to the commodity futures term-structure, consistently shows the strong and robust predictability for the future GDP growth especially in the long term.

As our empirical results shed light on the importance of the spreading factors in relation with the future economic state, we further analyze the predictability of the spreading factors in two ways. First, to examine whether the spreading factors subsume each other's predictability or which spreading factor has the strongest predictability, we conduct a horse race with spreading factors,  $BM^{spr}$ ,  $CR_H^{spr}$ ,  $CR_L^{spr}$ ,  $SL^{spr}$ , and  $CV^{spr}$ . We find that among these spreading factors, the slope spreading factor has the strongest and most robust predictability. These results also directly prove that the predictability of the basis-momentum spreading factor is mainly driven by the slope component, the slope spreading factor. Moreover, the predictive power of the high-basis spreading factor also appears to be subsumed by the slope spreading factor.

Second, as SRGN consider the long- and short-legs of the (basis) spreading factor separately, we additionally consider the long- and short-legs of the slope spreading factor. We further investigate whether one of these two lags of the slope spreading factor mainly leads predictability or whether they symmetrically play a critical role in predicting the future GDP growth. We find considerable differences between the long- and short-legs of the slope spreading factor. In specific, our results show that the robust long-term predictive power of the spreading factor mainly stems from the low-slope factor while the predictive power of the high-slope factor appears to be highly sensitive to the controlling variables. Moreover, in terms of the adjusted  $R^2$  values, we find the predictive power improves when the prediction model includes the two legs,  $SL_H^{spr}$  and  $SL_L^{spr}$ , separately. These results further imply that the long- and the short-legs of the slope spreading factor may have different information.

The remainder of the paper is organized as follows. Section 2 describes our data and Section 3 describes the commodity futures risk factors that we take account of. In Section 4, we examine the predictive power of commodity futures risk factors for future economic growth. Specifically, in Section 4.1, we focus on comparison of the predictive powers across commodity futures risk factors, and in Section 4.2, we examine the predictive power of commodity futures risk factors after controlling for traditional predictors. In Section 5, we further investigate the predictability of spreading factors. Lastly, Section 6 concludes the paper.

## 2. Data

In this paper, we use the Gross Domestic Product (GDP) growth as a measure of the economic growth following the majority of the literature (Lew and Vassalou, 2000; Vassalou, 2003; Kang and Kwon, 2017). The quarterly (seasonally adjusted) series of the GDP growth is obtained from the Organization for Economic Co-operation and Development (OECD).

The US Commodity futures data obtained from Datastream comprise daily settlement prices on 21 commodity futures contracts. Our data cover four major categories of commodities – namely, agriculture, energy, livestock, and metal – as in SRGN. Specifically, we include commodity futures contracts on feeder cattle, live cattle, corn, lean hogs, random lengths lumber, oats, rough rice, soybeans, soybean meal, soybean oil, wheat, cocoa, “C” coffee, cotton no. 2, frozen concentrated orange juice, light crude oil, heating oil, RBOB gasoline, high grade copper, gold, and silver.

We first compute monthly excess returns on a fully collateralized futures position. To compute the first-nearby return at month  $t+1$ , we take a position in the futures contract whose maturity is after the end of month  $t+1$  at the end of month  $t$ .<sup>1</sup> In a similar way, we also construct the time-series of the second-nearby returns for each commodity futures. Next, using the series of the first- and second-nearby returns, we construct two types of returns, one capturing the spot premium and the other one capturing the term premium, following SGRN and BP. The spot premium is captured by taking a long position in the first-nearby contract and the term premium is captured by taking a long position in the first-nearby contract and a short position in the second-nearby contract. Based on the monthly return series, we construct the quarterly factor series by rebalancing the portfolio every quarter and cumulating monthly returns in each quarter (see further details in Section 3). The daily data obtained from Datastream span

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<sup>1</sup> Our choice is consistent with that of the majority of commodity studies (Hong and Yogo, 2012; Gorton et al., 2012; BGR).

the period from January 1979 to December 2017, and the quarterly factor series span the period from the 1<sup>st</sup> quarter of 1980 (1980:1Q) to the 4<sup>th</sup> quarter of 2017 (2017:4Q).

In Section 4.2, we employ two sets of controlling predictors – one set of macroeconomic variables and another set of traditional risk factors in the equity market. For macroeconomic variables, we include the short-term interest rate (TB), term spread (TERM), default spread (DEF), and the variable CAY suggested by Lettau and Ludvigson (2000). In specific, we use the three-month Treasury bill rate for TB, the yield spread between 10-year government bonds and 1-year government bonds for TERM, and the yield spread between Moody’s BAA and AAA corporate bonds for DEF. CAY is a detrended wealth variable and the quarterly CAY data are provided by Lettau’s website.<sup>2</sup> For equity risk factors, we employ Fama and French’s (1993) three-factor model, which includes the market factor (RMRF), the size factor (SMB), and the value factor (HML).<sup>3</sup> The quarterly return series of these factors are obtained from French’s website.<sup>4</sup> In Sections 4.2 and 5, due to data availability of control variables, the sample period is limited from 1982:1Q to 2017:3Q. Lastly, following Liew and Vassalou (2000), all returns and growth rates used in this paper are continuously compounded.

### 3. Commodity futures risk factors

In this paper, we employ risk factors recently documented by BGR, SRGN, and BP, as they are unique to commodity futures markets and capture the spot and term premia related to the term structure of commodity futures. To construct those factors, we first define basis ( $B_t$ ) and momentum ( $M(t - 11, t)$ ) following BP:

$$B_t = \frac{F_t^{T_2}}{F_t^{T_1}} - 1 \quad \text{and} \quad M(t - 11, t) = \prod_{s=t-11}^t (1 + R_{fut,s}^{T_1}) - 1,$$

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<sup>2</sup> See <https://sites.google.com/view/martinlettau/data>.

<sup>3</sup> Since Liew and Vassalou (2000) document that SMB and HML have significant information about future GDP growth while the momentum factor does not, we employ Fama and French’s (1993) three factor model rather than Carhart’s (1997) four factor model which additionally includes the momentum factor.

<sup>4</sup> See [http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data\\_library.html](http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

where  $F_t^{T_i}$  indicates the  $i$  th-nearby futures price at month  $t$  and  $R_{fut,t}^{T_i}$  indicates  $i$  th-nearby futures return at month  $t$ .<sup>5</sup> Though BGR originally suggest the 6-month momentum factor, not the 12-month momentum factor, BP examine the 12-month momentum factor. As it is common to use the 12 month ranking period in the momentum literature, we employ the 12-month momentum ( $M(t - 11, t)$ ) but we also consider the 6-month momentum ( $M(t - 5, t)$ ) following the original method of BGR.

Basis-momentum ( $BM(t - 11, t)$ ) is defined as the difference between 12-month momentum in a first-nearby and second-nearby futures strategy.

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

BP document that basis-momentum can be decomposed into two components, the change in slope and the average curvature. Following BP, we define the change in slope and the average curvature as follows:

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

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

where  $B_s^{T_2}$  indicates the slope between the second- and third-nearby futures prices.

Using each of the above predictors, in each quarter  $t$ , we sort 21 commodities into three portfolios,  $p = \{\text{High4, Mid, Low4}\}$ . High4 (Low4) includes the four commodities with the highest (lowest) ranked signal and Mid includes remaining commodities. We construct portfolios based on the basis, the 12-month momentum, the 6-month momentum, the basis-momentum, the change in slope, and the average curvature, respectively. For each portfolio, we compute two types of returns following SRGN and BP, one capturing the spot premium and the other capturing the term premium. The spot premium is

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<sup>5</sup> In predictive regressions, we use log returns on portfolios as factors following Liew and Vassalou (2000), but in defining the variables to form portfolios, we follow the original methods using the normal returns, not log returns.

captured by taking a long position in the first-nearby contract and we call it a *nearby return*. The term premium is captured by taking a long position in the first-nearby contract and a short position in the second-nearby contract and we call it a *spreading return*. For each portfolio, we compute the equal-weighted average of nearby and spreading (log) returns of the portfolio for quarter  $t+1$ .

The SRGN model includes three factors: (1) the nearby return of the High4-minus-Low4 basis portfolio ( $CR^{nb}$ ), (2) the spreading return of the High4 basis portfolio ( $CR_H^{spr}$ ), and (3) the spreading return of the Low4 basis portfolio ( $CR_L^{spr}$ ). The BGR model includes three factors: (1) the average nearby return of all sample commodity futures ( $AVG^{nb}$ ), (2) the nearby return of the High4-minus-Low4 basis portfolio as in SRGN ( $CR^{nb}$ ) and (3) the nearby return of the High4-minus-Low4 momentum portfolio ( $MOM12^{nb}$  or  $MOM6^{nb}$  depending on the ranking period of momentum, which is 12 or 6 months, respectively). The BP model includes two factors: (1) the nearby return of the High4-minus-Low4 basis-momentum portfolio ( $BM^{nb}$ ) and (2) the spreading returns of the High4-minus-Low4 basis-momentum portfolio ( $BM^{spr}$ ).  $BM^{nb}$  ( $BM^{spr}$ ) can be further decomposed into two factors: (1) the nearby (spreading) return of the High4-minus-Low4 change in slope portfolio,  $SL^{nb}$  ( $SL^{spr}$ ), (2) the nearby (spreading) return of the High4-minus-Low4 curvature portfolio,  $CV^{nb}$  ( $CV^{spr}$ ).

[Insert Table 1 about here]

Table 1 presents the summary statistics of the factors constructed by SRGN, BGR, or BP. In addition, though BGR consider only nearby return factors, we also report the summary statistics of the spreading return factors, which are the average spreading return of all sample commodity futures ( $AVG^{spr}$ ), the spreading return of the High4-minus-Low4 basis portfolio ( $CR^{spr}$ ), and the spreading return of the High4-minus-Low4 momentum portfolio ( $MOM12^{spr}$  or  $MOM6^{spr}$  depending on the ranking period of momentum, which is 12 or 6 months, respectively).

Panel A of Table 1 shows the average, standard deviation, skewness, kurtosis, minimum, and maximum of quarterly factor values during the sample period. Consistent with SRGN and BP, Panel A shows that nearby return factors tend to be much larger than spreading return factors. For example, the

basis-momentum nearby factor ( $BM^{nb}$ ) has the mean of 1.651% while the basis-momentum spreading factor ( $BM^{spr}$ ) has the mean of 0.722%. In addition to the mean, in terms of the standard deviation, the nearby return factors show much larger standard deviations than spreading return factors. SRGN also report that the spreading return (term premium) tends to be of the opposite sign of the nearby return (spot premium), but our results show that in a quarterly basis the spreading and nearby return factors have the same signs in terms of the mean except the 12-month momentum.

Interestingly, the high-basis spreading factor ( $CR_H^{spr}$ ) and the low-basis spreading factor ( $CR_L^{spr}$ ) show substantial differences in distributions. The low-basis spreading factor shows much larger average and standard deviation than the high-basis spreading factor. SRGN document that the (High4-minus-Low4) basis spreading factor ( $CR^{spr}$ ) fails to explain various term premia, but if it is separated into two factors of the long leg ( $CR_H^{spr}$ ) and the short leg ( $CR_L^{spr}$ ) then these two factors successfully explain the term premia. Our results in later sections also suggest that  $CR_H^{spr}$  and  $CR_L^{spr}$  play different roles.

Panel B of Table 1 presents the correlations among commodity futures risk factors. The nearby and the spreading return factors of each predictor show correlations more than 40%. The correlation between the curvature factors is slightly low, which is 0.391, but the correlation between the average factors is notably low, which is 0.046. With respect to basis factors, the basis spreading factor shows a larger correlation with the short-leg, which is the low-basis spreading factor ( $CR_L^{spr}$ ). In specific, the correlation between  $CR^{spr}$  and  $CR_L^{spr}$  is -0.828 while the one between  $CR^{spr}$  and  $CR_H^{spr}$  is 0.549.

In general, Panel B suggests that commodity futures risk factors are substantially correlated with each other. For example, the basis-momentum nearby and the basis nearby factors have a correlation of -0.433 and the basis-momentum nearby and the momentum nearby factors have a correlation of 0.335. These results are in stark contrast to correlations between commodity futures risk factors and equity risk factors (reported in Table 4) as the correlations are less than 10% in absolute value in most of the cases. These results also support our motivation to focus on commodity futures risk factors in predicting future economic growth that are not explored yet and are expected to be distinguished from existing

factors, such as equity factors or macro-factors that are mainly examined in the previous studies (Liew and Vassalou, 2000; Vasslou, 2003).

#### 4. Can commodity risk factors predict GDP growth?

In this section, we examine whether commodity risk factors can predict the future GDP growth. We basically use the following quarterly regression model:

$$GDP\ growth_{t+1Q,t+hQ} = \alpha + \beta' F_t + \delta' C_t + \varepsilon_t \quad (1)$$

where  $GDP\ growth_{t+1Q,t+hQ}$  indicates the GDP growth for future  $h$  quarters from quarter  $t+1Q$  to quarter  $t+hQ$  for  $h = 1$  to  $8$ ,  $F_t$  indicates the set of commodity futures risk factors at quarter  $t$ , and  $C_t$  is the set of control variables at quarter  $t$ . In Section 4.1, we consider only commodity futures risk factors with no control variables ( $C_t$ ) in the regression model. In Section 4.2, we consider two sets of control variables – one set of macroeconomic variables and another set of traditional equity risk factors – and examine whether commodity futures risk factors show significant predictability even after controlling for these existing predictors.

##### 4.1. Predictability of commodity risk factors

We first run a univariate regression with each of commodity futures risk factors. Next, we examine multivariate regression models that include a subset of commodity futures risk factors in our consideration. In Table 2, we report the coefficient on the commodity futures risk factor, its statistical significance ( $t$ -statistics), and the adjusted  $R^2$  of the regression to see the explanatory power.

[Insert Table 2 about here]

Table 2 exhibits that most of commodity futures risk factors fail to predict the future economic growth. First, in Table 2, all nearby return factors except the basis-momentum, average, and 12-month

momentum factors, show insignificant coefficients and even negative adjusted  $R^2$  for all horizons. Moreover, the predictability of  $BM^{nb}$  is only limited to the next first quarter. Specifically, the coefficient on  $BM^{nb}$  is marginally significant ( $t$ -statistics = 1.71) only for  $h=1$  and it becomes insignificant in longer terms. By contrast, the average nearby factor shows stronger predictability up to five quarters. The results show that its predictability for the future GDP growth decreases as  $h$  increases. In case of  $h=1$ , the adjusted  $R^2$  is 9.07% which is the largest among all commodity futures risk factors, and the adjusted  $R^2$  monotonically decreases as  $h$  increases. However, the coefficients of  $AVG^{nb}$  are significant up to the next five quarters ( $h=5$ ).

While two nearby factors,  $BM^{nb}$  and  $AVG^{nb}$ , show positive and significant results in a short term, the 12-month momentum nearby factor shows a different pattern.  $MOM12^{nb}$  shows the negatively significant relation with the future GDP growth from  $h=6$ . The negative relation between  $MOM12^{nb}$  and the future GDP growth is consistent with findings of Kang and Kwon (2017), but the interesting feature is that Panel B of Table 1 shows that  $MOM12^{nb}$  are positively correlated with  $BM^{nb}$  and  $AVG^{nb}$  that positively predict the GDP growth. Previously, BGR investigate the economic interpretation of the basis nearby factor ( $CR^{nb}$ ) and the momentum nearby factor ( $MOM6^{nb}$ ), and report that these two factors capture different risks in the financial markets.<sup>6</sup> We expect that  $MOM12^{nb}$ ,  $BM^{nb}$ , and  $AVG^{nb}$  may capture different risks though they are positively correlated with each other, and thus show considerable differences in predicting economic growth. However, it is beyond the focus of this paper, and thus we leave it for future research.

The spreading return factors show better predictability than the nearby return factors in the long term. For example,  $BM^{spr}$  negatively predicts the next four to eight quarter GDP growth, and  $CR_H^{spr}$  positively predicts the next five to eight quarter GDP growth. Both factors show that the size of coefficients and the adjusted  $R^2$  values monotonically increase as the horizon ( $h$ ) extends in general. SRGN argues that the long- and short-legs of the basis spreading factor, the high-basis and the low-

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<sup>6</sup> More specifically, they argue that the basis nearby factor is related to global equity volatility and the momentum nearby factor is related to speculative activity in the commodity futures market.

basis spreading factors, play distinct roles especially in explaining the term premia. Consistent with SRGN, our results imply the different roles of these two factors in predicting future economic growth. Only  $CR_H^{spr}$  shows the significant predictability for the future GDP growth. More specifically, for two-year (eight-quarter) growth,  $CR_H^{spr}$  significantly predicts it with the adjusted  $R^2$  of about 3%.

$BM^{spr}$  can be decomposed to the change in slope factor ( $SL^{spr}$ ) and the average curvature factor ( $CV^{spr}$ ). Among these two factors, we find that the predictability of  $BM^{spr}$  mainly stems from the change in slope factor. In specific,  $SL^{spr}$  negatively predicts the future GDP growth and its coefficients are even negatively larger and more significant than those of  $BM^{spr}$ . The adjusted  $R^2$  values also imply that  $SL^{spr}$  better predicts the future GDP growth than  $BM^{spr}$ . In case of  $SL^{spr}$ , the adjusted  $R^2$  values range from -0.24% to 4.64%, and especially for long horizons they are all over 3%. In case of  $BM^{spr}$ , the adjusted  $R^2$  values are at most 2.16%. These results seem interesting because BP highlight that though both the curvature and the change in slope contribute to the pricing effect of basis-momentum, the curvature component contributes much more. By contrast, as a state variable in the context of Merton's (1973) ICAPM, our results suggest the importance of the change in slope (spreading) factor containing information about the future economic state rather than the curvature (spreading) factor.

Lastly, the most of the adjusted  $R^2$  values reported in Table 2 seem quite small even for the significant cases. However, Harvey (1989) report that the equity market factors can explain only about 5 percent of the variation of the future GDP growth. In fact, as we report in Panel A of Tables 5 and 6, the macroeconomic variables and equity market factors also provide the adjusted  $R^2$  values comparable to those of commodity futures risk factors. For example, the equity value factor (HML) can explain at most 1.99% and the term spread (TERM) can explain at most 6.09%. Hence, the significant relations between some of commodity futures risk factors and the future GDP growth in Table 2 do not seem to be ignorable.

Next, we run multivariate regressions with various subsets of commodity futures risk factors. Specifically, in Eq. (1),  $F_t$  is a set of commodity futures risk factors and there is no controlling variables ( $C_t$ ). We basically consider the BP, the SRGN, and the BGR models. Model 1 is the BP's model

including the basis-momentum nearby and spreading factors, and Model 2 is a BP's extended model which includes the average nearby factor in addition to the BP factors. Model 3 is the SRGN model including the basis nearby factor, the high- and low-basis spreading factors. Models 4 and 5 are the BGR models – including the average, basis, and momentum nearby factors – with the 12- and 6-month momentum nearby factors, respectively. Models 6 and 7 are the decomposed BP models – including the change in slope nearby and spreading factors, and the average curvature nearby and spreading factors – without and with the average nearby factor, respectively. By running multivariate regression, we expect to see whether the predictability of a factor is subsumed by that of another or a set of factors can improve the predictability for future economic growth by jointly working as state variables. We report the estimated results in Table 3.

[Insert Table 3 about here]

Overall results in Table 3 are qualitatively similar to the univariate results in general though the size and significance of coefficients show some differences. First, according to the estimated results of Models 1 and 2, the short-term predictability of the basis-momentum nearby factor ( $BM^{nb}$ ) and the long-term predictability of the basis-momentum spreading factor ( $BM^{spr}$ ) do not critically affect each other.  $BM^{spr}$  appears to be highly significant in the long term as we find in the univariate regression regardless of including  $BM^{nb}$  or/and  $AVG^{nb}$ . The effect of  $BM^{nb}$  becomes weaker as  $AVG^{nb}$  is included but still remains significant. In Model 3, consistent with Table 2, only  $CR_H^{spr}$  shows the significant predictability for the future GDP growth while it is slightly more significant than the univariate cases. Models 4 and 5 show that momentum nearby factors based on the past 12 and 6 months have substantial differences in predicting the future GDP growth, which is also consistent with the univariate cases. With regard to the two components of the basis-momentum, Model 6 reports that predictability of  $SL^{spr}$  is not largely affected by controlling for other components,  $SL^{nb}$ ,  $CV^{nb}$ , and  $CV^{spr}$ .

However, Table 3 also exhibits some interesting differences compared to the univariate cases. The coefficients on  $AVG^{nb}$  show dramatic changes compared to the univariate results. In Table 2, we

find that the coefficients on  $AVG^{nb}$  are significant up to five quarters ( $h=5$ ), but in Table 3, we find that after controlling for the basis-momentum nearby and spreading factors, they are significant up to seven quarters ( $h=7$ ). Compared to Model 1, Model 2 shows the improved predictability for all horizons and  $BM^{spr}$  in Model 2 also exhibits slightly more significant results compared to Model 1 in Table 3 and the univariate results in Table 2. These results suggest that  $AVG^{nb}$  and  $BM^{spr}$  can better jointly work as state variables in the context of Merton's (1973) ICAPM. This improvement of predictability in the multivariate models, is also observed in Models 4 and 7. Specifically, Model 4 shows that the predictability of  $AVG^{nb}$  and  $MOM12^{nb}$  is improved especially in the long term compared to the univariate results. In Model 7, if  $AVG^{nb}$  is included, the coefficients on  $SL^{spr}$  become more significant and consequently appear to be significant over all test horizons.  $AVG^{nb}$  also generally shows improved results over all horizons except in the short term, especially in case of  $h=1$ . In specific, the univariate results (Table 2) report that the coefficient on  $AVG^{nb}$  in case of  $h=1$  is 0.091 with  $t$ -statistics = 2.11 while the multivariate results (Model 7 in Table 3) show that it is 0.074 with  $t$ -statistics = 1.77. These results suggest that there can be a subset of commodity futures factors that show the improved predictability if jointly considered.

Overall, the multivariate regressions provide the qualitatively similar results as the univariate regressions. We find that in the short term within a year the average and the basis-momentum nearby factors show significant results and in the longer term from one to two years the 12-month momentum nearby factor and the basis-momentum and high-basis spreading factors show significant results. Moreover, between the change in slope and the average curvature spreading factors, the change in slope factor appears to be the main driver of the basis-momentum spreading factor's predictability. Lastly, multivariate results also suggest that there can be a subset of commodity futures factors that show the improved predictability if jointly considered; for example,  $AVG^{nb}$  and  $BM^{spr}$ ,  $AVG^{nb}$  and  $MOM12^{nb}$ , and  $AVG^{nb}$  and  $SL^{spr}$ .

## 4.2. Do other predictors subsume predictability of commodity risk factors?

In this section, we further consider other traditional predictors for future economic growth and examine the predictability of commodity risk factors after controlling for these traditional predictors. In specific, we employ two sets of controlling predictors – one set of macroeconomic factors and another set of traditional risk factors in the equity market. For macroeconomic factors, we include the short-term interest rate (TB), term spread (TERM), default spread (DEF), and the variable CAY suggested by Lettau and Ludvigson (2000). In specific, we use the three-month Treasury bill rate for TB, the yield spread between 10-year government bonds and 1-year government bonds for TERM, and the yield spread between Moody’s BAA and AAA corporate bonds for DEF. These variables are often used to capture the business cycle of the economy (Fama and French, 1989; Liew and Vassalou, 2000; Kang et al., 2012). CAY is a detrended wealth variable. For equity risk factors, we employ Fama and French’s (1993) three-factor model, which includes the equity market factor (RMRF), the size factor (SMB), and the value factor (HML). In this section, due to data availability of control variables, the sample period is limited to the shorter period, which is from 1982:1Q to 2017:3Q.

[Insert Table 4 about here]

First, we investigate the correlations among commodity futures risk factors and control variables. Overall results in Table 4 confirm our motivation to focus on commodity futures risk factors that are not explored yet and are expected to be distinguished from existing factors, such as equity factors or macroeconomic factors that are mainly examined in the previous studies (Harvey, 1989; Liew and Vassalou, 2000; Vassalou, 2003). As we note in Section 2, compared to the correlations among commodity futures risk factors (Panel B of Table 1), commodity futures risk factors show relatively low correlations with both macroeconomic factors and equity risk factors. The correlations between commodity futures risk factors and equity risk factors are less than 10% in absolute value in most of the cases. However, it is notable that  $AVG^{nb}$  and RMRF are positively correlated. The correlation is largest among all correlations between commodity futures risk factors and control variables, which is

0.215. This suggests that the equity market factor and the commodity futures market factor are positively and substantially correlated. In addition,  $BM^{nb}$  appears to be more correlated with macroeconomic factors, especially with TB and DEF, than with equity risk factors.

On the other hand, equity risk factors generally show relatively larger correlations with each other and also with macroeconomic factors than with commodity futures factors. For example, the correlation between RMRF and SMB is 0.444 and the one between RMRF and DEF is -0.213. Except the correlation between TERM and CAY, the correlations among macroeconomic factors appear to be relatively large ranging from 0.266 to 0.546 in absolute value.

Next, we investigate the predictability of commodity futures risk factors after controlling for each of two sets of controlling predictors. More specifically, in Eq. (1),  $F_t$  is each individual commodity futures risk factor<sup>7</sup> and  $C_t$  is a set of controlling variables, either a set of macroeconomic factors or a set of equity risk factors. We first examine the marginal predictability of commodity futures risk factors after controlling for macroeconomic factors (Table 5), and then we examine it after controlling for equity risk factors (Table 6).

[Insert Table 5 about here]

First, Panel A of Table 5 presents the univariate and multivariate predictive regressions with only macroeconomic factors. The macroeconomic factors exhibit rather weak results in the univariate models except DEF as it shows significant results up to four quarters and the adjusted  $R^2$  appears to be large especially in short term (for example, 17.94% in case of  $h=1$ ). The multivariate model suggests that the macroeconomic factors might jointly work as state variables. In the multivariate model, in addition to DEF, TERM also shows a significant relation with future economic growth even in the longer term up to eight quarters, and the adjusted  $R^2$  also shows much improved results compared to the univariate

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<sup>7</sup> In this section, for  $F_t$ , we use each individual commodity futures risk factor rather than a subset of commodity futures risk factors as the multivariate regression models in Table 3 because in the previous section we find that the univariate and the multivariate results are qualitatively similar. We find that using a subset of commodity futures risk factors also provides similar results, and thus we report only the results using individual commodity futures risk factor in this section.

model with DEF. The improvement in the adjusted  $R^2$  seems to be notable especially in the long term as it increases from 6.09% to 10.41% in case of  $h = 8$ .

Panel B of Table 5 shows the multivariate results with each of commodity futures risk factors and a set of macroeconomic factors. The common feature in Panel B is that the coefficient of the commodity futures risk factor for the next quarter ( $h=1$ ) is reduced a lot and becomes much less significant compared to the univariate results in Table 2. In fact, the commodity futures factors that show significant predictability in the short term in the previous analyses appear to be insignificant, which indicates that their predictability is subsumed by macroeconomic variables. More specifically, in Section 4.1, we find that in the short term the average and the basis-momentum nearby factors show significant results, however, after controlling for macroeconomic factors, both show no significant predictability over all test horizons. For example,  $AVG^{nb}$  exhibits the largest and most significant coefficient for  $h=1$  in Table 2 (coefficient = 0.091 with  $t$ -statistics = 2.11), but after controlling for macroeconomic factors, it becomes 0.0003 with  $t$ -statistics = 0.87.

By contrast, the commodity futures factors that exhibit significant results in the long term in the previous analyses are found to be robust to macroeconomic factors. In specific, we previously find that  $MOM12^{nb}$ ,  $BM^{spr}$ , and  $CR_H^{spr}$  have significant predictability in the long term. In addition, between the change in slope and the average curvature components of  $BM^{spr}$ , the change in slope component appears to mainly contribute to its predictability. In Table 5, they show slightly weaker results compared to the results in Table 2, but many of their coefficients remain significant especially from  $h=5$  to 8. The coefficients on  $BM^{spr}$  from  $h=5$  to 8 range from -0.063 to -0.097 and their  $t$ -statistics range from -1.74 to -2.58.  $SL^{spr}$  also shows a significant relation with the future GDP growth from  $h=6$  to 8 and it also substantially improves the adjusted  $R^2$  relative to the macroeconomic-factor-only model. For example, in case of  $h=8$ , Panel A of Table 5 reports that the multivariate macroeconomic model generates the adjusted  $R^2$  of 10.41%, but Panel B of it shows that if  $SL^{spr}$  is additionally included, the adjusted  $R^2$  is improved to 13.26%.

In Table 3, from the multivariate regressions, we find that the predictability of  $BM^{spr}$ ,  $MOM12^{nb}$ , and  $SL^{spr}$  is improved if  $AVG^{nb}$  is included in the model, and Table 5 shows that the predictability of  $AVG^{nb}$  is subsumed by the macroeconomic factors. Though the coefficients on  $BM^{spr}$ ,  $MOM12^{nb}$ , and  $SL^{spr}$  become statistically weaker in Table 5 compared to the results in Table 3, the improved adjusted  $R^2$  values in Table 5 still suggest that  $BM^{spr}$ ,  $MOM12^{nb}$ , and  $SL^{spr}$  contain information about the future state of the economy over the information contained in  $AVG^{nb}$  or the macroeconomic factors, and can jointly play a role as state variables with the macroeconomic factors.

Overall results in Table 5 provide interesting implications. The commodity futures risk factors that previously show significant predictability for the future GDP growth in short term –  $AVG^{nb}$  and  $BM^{nb}$  – show insignificant results over all test horizons after controlling for macroeconomic factors. These results suggest that the economic source of these factors are related to macroeconomic factors, and thus their predictability is subsumed by these variables. By contrast, the commodity futures risk factors that have significant predictability in longer term –  $MOM12^{nb}$ ,  $BM^{spr}$ ,  $CR_H^{spr}$ , and  $SL^{spr}$  – remain significant even after controlling for macroeconomic factors. These results may imply that the economic source of these factors are different from macroeconomic factors.

[Insert Table 6 about here]

Next, we control for traditional equity risk factors. In Panel A of Table 6, we first examine the predictability of equity risk factors for comparison. The equity market factor, RMRF, exhibits the strongest predictability among three factors in both the univariate and multivariate regressions. The coefficients on RMRF are positively significant in all test horizons, the adjusted  $R^2$  value decreases as the forecast horizon ( $h$ ) is extended. The value factor, HML, shows a significant coefficient only for  $h = 8$  in the univariate model, but in the multivariate model including all three equity factors, it shows significant results in more cases ( $h = 5$  to  $8$ ). Compared to the multivariate model of macroeconomic factors in Panel A of Table 5, that of equity risk factors shows relatively low adjusted  $R^2$  values that range from 8.06% to 13.99%. This is also consistent with Harvey's (1989) finding that macroeconomic factors show much better performance in predicting the future GDP growth than equity factors.

As in Panel B of Table 5, in Panel B of Table 6, we test the multivariate models of which independent variables are one of the commodity futures risk factors and a set of three equity factors. One of the common features in Panel B of Tables 5 and Table 6 is that the coefficient of the commodity futures risk factor for the next quarter ( $h=1$ ) is reduced a lot and becomes much less significant compared to the univariate results in Table 2. Another common feature is that the predictability of  $AVG^{nb}$  becomes insignificant in both models. Panel B of Table 6 shows that the coefficients on  $AVG^{nb}$  are insignificant in all cases ( $t$ -statistics = -0.38 to 1.05). By contrast, another short-term predictor,  $BM^{nb}$  remains significant at least for the next quarter ( $h=1$ ). Panel A of Table 4 indeed suggests some differences between  $AVG^{nb}$  and  $BM^{nb}$ .  $AVG^{nb}$  and  $BM^{nb}$  show comparable correlations with some of macroeconomic factors, especially with DEF, but  $BM^{nb}$  shows much lower correlations with all three equity factors ranging from -0.051 to 0.019 while the correlation between the two market factors,  $AVG^{nb}$  and RMRF is 0.215. In addition to our findings in Panel B of Table 5, Panel B of Table 6 additionally suggests the different nature of  $AVG^{nb}$  and  $BM^{nb}$ .  $AVG^{nb}$  seems to be more correlated with the equity market risk, and  $BM^{nb}$  might be more related to the commodity futures market's own risk related to the macroeconomic state.

The equity factor and macroeconomic models also generate other substantial differences. First, the predictability of  $MOM12^{nb}$  after controlling for equity factors is in stark contrast to that after controlling for macroeconomic factors. Previously, Table 3 exhibits that  $BM^{spr}$ ,  $MOM12^{nb}$ , and  $SL^{spr}$  seem to be able to jointly work with  $AVG^{nb}$  as state variables and in Table 5 we also find that they can jointly play a role as state variables with the macroeconomic factors that subsume the predictability of  $AVG^{nb}$ . However, Panel B of Table 6 shows that  $MOM12^{nb}$  becomes insignificant while other two factors,  $BM^{spr}$  and  $SL^{spr}$ , show significant results. These results might suggest that the predictability of  $MOM12^{nb}$  is subsumed by the information content unique to the equity risk factors.

Second,  $BM^{spr}$  presents relatively weaker but still significant results after controlling for equity risk factors. However, if its components - the change in slope and the average curvature - are separately considered, only the change in slope ( $SL^{spr}$ ) shows highly significant results in all cases except  $h=1$ .

$SL^{spr}$  notably improves the adjusted  $R^2$  values in long-term horizons. In specific, the equity multivariate model in Panel A of Table 6 shows that the adjusted  $R^2$  value for  $h=8$  is 8.06% while it increases to 11.73% in Panel B of Table 6 if  $SL^{spr}$  is additionally included. In fact, the improvement of the adjusted  $R^2$  in long term appears to be largest with  $SL^{spr}$  among all commodity futures risk factors.

Lastly,  $CR_H^{spr}$  also reveals substantial differences between the equity and macroeconomic factor models in Tables 5 and 6, respectively. In Table 6, the only significant case is with  $h=8$ , and even in that case it is marginally significant ( $t$ -statistics = 1.68). The other component of the basis spreading factor,  $CR_L^{spr}$ , exhibits an interesting feature. Compared to the univariate results in Table 2, the coefficients on  $CR_L^{spr}$  are reduced much and become even negative. Consequently,  $CR_H^{spr}$  positively predicts the future GDP growth and  $CR_L^{spr}$  negatively predicts the future GDP growth though the coefficients are not statistically significant. These results suggest that decomposing  $CR^{spr}$  into its long and short legs and using those legs as two independent factors may improve the predictability for future economic growth. In previous analyses,  $CR^{spr}$  consistently shows the insignificant predictive power for the future GDP growth. After controlling for equity risk factors, however,  $CR^{spr}$  positively and significantly predicts the future GDP growth from  $h=5$  to 8. SRGN document that the long- and the short-legs of  $CR^{spr}$  should be separately considered to explain the term premia of commodity futures. It is because the equity market-related risks asymmetrically affect the long- and the short-legs of  $CR^{spr}$ . Our results show that by controlling for equity risk factors,  $CR^{spr}$  more effectively captures the differences between the long- and the short-legs, and  $CR^{spr}$  might be able to act as a state variable jointly with equity risk factors.

To sum up, the predictive power of commodity futures risk factors shows substantial differences between the cases with and without controlling for existing traditional predictors. In the previous section, we find that  $AVG^{nb}$  and  $BM^{nb}$  significantly predict the future GDP growth in the short term and  $MOM12^{nb}$ ,  $BM^{spr}$ ,  $CR_H^{spr}$ , and  $SL^{spr}$  predict in the long term. In this section, we find that only the long-term predictors remain significant after controlling for macroeconomic factors. After controlling for equity risk factors,  $BM^{nb}$ ,  $BM^{spr}$ , and  $CR_H^{spr}$  remain significant but become much weaker. The

most impressive finding is that  $SL^{spr}$  consistently shows strong and robust predictability for the future GDP growth especially in the long term.

The commodity risk factors that show significant results in both analyses, controlling for macroeconomic factors and equity risk factors, are all spreading return factors,  $BM^{spr}$ ,  $CR_H^{spr}$ , and  $SL^{spr}$ . The literature on commodity futures has been mainly focused only on nearby returns capturing the spot premia before the pioneering work of SRGN leads to two sources of returns in commodity futures, the spot and term premia. SRGN also report that the term premia captured by the spreading return are generally much smaller in size but more challenging to be explained by the factor model than the spot premia captured by the nearby return. Our results show that the predictive power of commodity futures nearby return factors for the future GDP growth is subsumed by existing factors, either macroeconomic factors or equity risk factors. Our results also highlight the importance of spreading return factors, especially related to the shape of commodity futures term structure, as a state variable in the context of Merton's (1973) ICAPM. They seem to embody an economic source unique to commodity futures markets and also significantly predict future economic growth.

## 5. Further analyses on term premia

In this section, we focus on spreading factors and further investigate their predictive power for future economic growth. Previously, we find that spreading factors show the robust predictability for the future GDP growth even after controlling for macroeconomic or equity risk factors. However, whether they subsume each other's predictability or which a specific factor contains information for future economic state unique to other spreading factors is not yet examined. In this section, we conduct a horse race with spreading factors to investigate these issues.

In Section 4, we find that three spreading factors,  $BM^{spr}$ ,  $CR_H^{spr}$ , and  $SL^{spr}$ , show the robust predictability for the future GDP growth, and thus we examine these three robust spreading factors. In addition, we include  $CR_L^{spr}$  and  $CV^{spr}$  in the set of predictors for comparison as they are the other

component, respectively, when we decompose the basis spreading factor and the basis-momentum spreading factor into two factors. Panel B of Table 1 exhibits considerable correlations among these spreading factors<sup>8</sup>, which implies that including all these factors would negatively affect their respective predictive power but we expect that it will be a more thorough test in the conservative perspective to figure out the strongest and most robust predictor among them.

Specifically, we include  $BM^{spr}$ ,  $CR_H^{spr}$ ,  $CR_L^{spr}$ ,  $SL^{spr}$ , and  $CV^{spr}$  for  $F_t$  in Eq (1). Model 1 in Table 7 includes no controlling variable ( $C_t$ ), and Models 2 and 3 in Table 7 include controlling variables. As in Section 4.2, Model 2 includes macroeconomic factors, TB, TERM, DEF, and CAY, and Model 3 includes equity risk factors, RMRF, SMB, and HML as controlling variables.<sup>9</sup>

[Insert Table 7 about here]

First, Model 1 in Table 7 exhibits that only the slope spreading factor ( $SL^{spr}$ ) has significant predictive power in the long term. Compared to the univariate results in Table 2, our results report that all factors show substantially reduced predictability.  $SL^{spr}$  also shows considerable decrease in predictability, but it still remains significant. For example, Table 2 shows that from  $h=4$  to 8 the coefficients on  $SL^{spr}$  have  $t$ -statistics of -2.83 to -3.79, while in Model 1 of Table 7, they range only from -1.67 to -2.13. However, the most notable finding from this horse race is that  $SL^{spr}$  is the only spreading factor which remains significant. In Model 2 in Table 7,  $SL^{spr}$  shows the further reduced predictability after controlling for macroeconomic factors. In fact, the coefficients on  $SL^{spr}$  appear to be significant only for  $h=7$  and 8. Though Model 2 exhibits the highly reduced predictive power of  $SL^{spr}$ , it is still the only predictor that shows significant results. In Model 2, except  $SL^{spr}$ , no factor shows significant results. Lastly, the results in Model 3 are in stark contrast to those in Model 2. After controlling for equity risk factors,  $SL^{spr}$  shows significant results for all test horizons. In specific, its

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<sup>8</sup> For example, the correlation between  $BM^{spr}$  and  $SL^{spr}$  is 0.482 and the one between  $BM^{spr}$  and  $CR_L^{spr}$  is 0.406.

<sup>9</sup> Moreover, in Section 4.1, from the multivariate analyses, we find that there are pairs of commodity futures factors that show the improved predictability if jointly considered:  $AVG^{nb}$  and  $BM^{spr}$ , and  $AVG^{nb}$  and  $SL^{spr}$ . However, in Section 4.2, we additionally confirm that the predictability of  $AVG^{nb}$  is subsumed by macroeconomic factors or equity factors. As we control for macroeconomic factors or equity risk factors in Models 2 and 3 in Table 7, we expect that the joint effects can be also considered by including these control variables.

predictive power appears to be lower and less significant for  $h=1$  (coefficient = -0.001 with  $t$ -statistics = -1.89), but for all longer horizons, from  $h=2$  to 8, the  $t$ -statistics on the coefficients are larger than 2.15 in absolute value. More importantly, consistent with Models 1 and 2, only  $SL^{spr}$  shows the significant predictive power among test spreading factors.

To summarize, our results from the horse race among spreading factors indicate that the slope spreading factor is the strongest and most robust predictor among them. These results imply that the slope spreading factor subsumes the predictive power of other spreading factors, and contains information for future economic state unique to other spreading factors and also traditional predictors. These results also confirm our interpretation in the previous analyses that the predictability of the basis-momentum spreading factor is mainly driven by the slope component, the slope spreading factor. Moreover, the significant predictive power of the high-basis spreading factor observed in the previous analyses also appears to be subsumed by the slope spreading factor.

Interestingly, the difference in the predictability of  $SL^{spr}$  in Models 2 and 3 of Table 7 is similar to the one in the predictability of  $CR^{spr}$  in Panel B of Tables 5 and 6. In Tables 5 and 6, we find that the predictive power of  $CR^{spr}$  becomes weaker after controlling for macroeconomic factors while it becomes stronger after controlling for equity factors. In Models 2 and 3 of Table 7, the predictive power of  $SL^{spr}$  shows the similar pattern. Furthermore, by investigating the predictability of the long- and short-legs of the basis spreading factor ( $CR_H^{spr}$  and  $CR_L^{spr}$ ) independently, we conclude that the equity market-related risks seem to asymmetrically affect the long- and the short-legs of  $CR^{spr}$ , and  $CR^{spr}$  more effectively captures the differences between the long- and the short-legs under control of the effects of equity risk factors. Our results also suggest that  $CR^{spr}$  might be able to act as a state variable jointly with equity risk factors.

Motivated these previous findings and similarity between  $SL^{spr}$  and  $CR^{spr}$ , we examine the long- and short-legs of the slope spreading factor as two independent factors. In specific, while we only separate the basis spreading factor into two legs following SRGN in the previous sections, we also disentangle the slope spreading factor into two legs in predicting the future GDP growth to investigate

whether one of them mainly leads predictability or whether they symmetrically play a critical role in predicting the future GDP growth.

We consider three models including the high-slope spreading factor, the low-slope spreading factor, and both the high- and low-slope spreading factors ( $SL_H^{spr}$  and  $SL_L^{spr}$ , respectively) as  $F_t$  in Eq. (1), respectively. In Table 8, Models 1, 4, and 7 (Models 2, 5, and 8) are the ones with the high-slope (low-slope) spreading factor, and Models 3, 6, and 9 are the ones with both the high- and low-slope spreading factors. In addition, for controlling variables ( $C_t$ ) in Eq. (1), Models 1, 2, and 3 include no controlling variables, and Models 4, 5, and 6 (Models 7, 8, and 9) include macroeconomic factors, TB, TERM, DEF, and CAY (equity risk factors, RMRF, SMB, and HML).

[Insert Table 8 about here]

Interestingly, Table 8 exhibits considerable differences in predictability of  $SL_H^{spr}$  and  $SL_L^{spr}$ . First, without any controlling variables, Models 1 and 2 show that the predictive power of  $SL_H^{spr}$  is mainly concentrated on the intermediate horizons, mainly from  $h=3$  to 5, while that of  $SL_L^{spr}$  is mainly concentrated on the longer horizons, from  $h=6$  to 8. Model 3 shows that in the multivariate case the coefficients on  $SL_H^{spr}$  in the long term becomes slightly more significant, but the adjusted  $R^2$  values clearly show that the long-term predictability is attributed to  $SL_L^{spr}$ . For example, for  $h=8$ , Model 2 reports the adjusted  $R^2$  value of 4.67% while Models 1 and 3 report that of 0.50% and 5.35%, respectively.

After controlling for other effects, either the effect of the macroeconomic factors or the effect of the equity risk factors, the coefficients on  $SL_H^{spr}$  show dramatic changes whereas those on  $SL_L^{spr}$  show only small differences. In specific, after controlling for the macroeconomic factors, Models 4 and 6 present insignificant coefficients on  $SL_H^{spr}$  in all cases. By contrast, long-term predictability of  $SL_L^{spr}$  remains significant, and the adjusted  $R^2$  values for  $h=7$  and 8 also seem notable. In Table B of Table 5, if the slope spreading factor is included with the set of macroeconomic factors, the adjusted  $R^2$  value for  $h=8$  is 13.26%. Model 5 in Table 7 shows that if the low-slope spreading factor is included instead

of the slope spreading factor, it is improved to 13.98%. Moreover, if the high- and low-slope spreading factors are separately included, Model 6 in Table 7 shows a small but further increase in the adjusted  $R^2$  value, which is 14.11%. Consistent with our findings in Models 1 to 3, Models 4 to 6 further suggest that the predictive power of the slope spreading factor mainly stems from that of the low-slope spreading factor.

After controlling for the equity risk factors, Models 7 to 9 report that the coefficients on  $SL_H^{spr}$  are highly significant in most cases as opposed to those in Models 4 to 6. These dramatic changes in the predictive power of  $SL_H^{spr}$  depending on the controlling variables are quite similar to these of  $SL^{spr}$  in Tables 5 and 6. We previously find that the predictive power of  $SL^{spr}$  becomes stronger after controlling for the equity factors (Table 6) whereas it becomes much weaker after controlling for the macroeconomic factors. However, more importantly, our conclusion in the previous analyses is that the most robust results are observed in the long term. Table 8 additionally shows that the robust long-term predictive power is observed from  $SL_L^{spr}$  and predictability of  $SL_H^{spr}$  appears to be highly sensitive to controlling variables. Moreover, in the long term,  $SL_L^{spr}$  shows the larger adjusted  $R^2$  value than  $SL_H^{spr}$ . For example, in case of  $h=8$ , Model 8 reports the adjusted  $R^2$  value of 12.46% and Model 7 reports that of 10.08%.

Our results in Table 8 suggest the considerable differences between the long- and short-legs of the slope spreading factor as we find the differences between these of the basis spreading factor. Our results show that the robust long-term predictive power of  $SL^{spr}$  seems to be mainly associated with  $SL_L^{spr}$  while the predictive power of  $SL_H^{spr}$  appears to be highly sensitive to other controlling variables. Moreover, in terms of the adjusted  $R^2$  values, we find the improved results from the model including the two legs,  $SL_H^{spr}$  and  $SL_L^{spr}$ , separately. These results further imply that the long- and the short-legs of the slope spreading factor play different roles in predicting future GDP growth.

## 6. Conclusion

This paper examines whether commodity futures risk factors can predict the future GDP growth. We find that  $AVG^{nb}$  and  $BM^{nb}$  significantly predict the future GDP growth in the short term and  $MOM12^{nb}$ ,  $BM^{spr}$ ,  $CR_H^{spr}$ , and  $SL^{spr}$  predict in the long term before controlling for other effects. However, after controlling for other effects, we find that only the long-term predictors remain significant. More specifically, only three spreading factors,  $BM^{spr}$ ,  $CR_H^{spr}$ , and  $SL^{spr}$ , remain significant.

The literature on commodity futures has been mainly focused only on nearby returns before the pioneering work of SRGN leads to two sources of returns in commodity futures, the spot and term premia. SRGN also report that the term premia captured by the spreading return are generally much smaller in size but more challenging to be explained by the factor model than the spot premia captured by the nearby return. Our results show that the predictive power of commodity futures nearby return factors for the future GDP growth is subsumed by existing factors, either macroeconomic factors or equity risk factors. Instead, our findings stress the importance of spreading return factors as risk factors unique to the commodity futures markets.

The horse race with spreading factors exhibits that the slope spreading factor is the strongest and most robust predictor among them. Moreover, if the long- and short-legs of the slope spreading factor are separately considered, then the robust long-term predictive power of  $SL^{spr}$  seems to be mainly driven by  $SL_L^{spr}$  while the predictive power of  $SL_H^{spr}$  appears to be highly sensitive to other controlling variables. Moreover, in terms of the adjusted  $R^2$  values, we find the improved results when the model is extended to the one when the two legs,  $SL_H^{spr}$  and  $SL_L^{spr}$ , are separately included as independent variables. These results further imply that the long- and the short-legs of the slope spreading factor play different roles in predicting future economic growth.

The main goal of this paper is to examine the predictive power of the existing commodity futures risk factors as Liew and Vassalou (2000) examine that of the equity risk factors, and thus the long- and short-legs of the slope spreading factor are not indeed of our main interests. However, though BP do not originally suggest to consider the long- and short-legs of their factors (especially the spreading

factors) independently, in the context of Merton's (1973) ICAPM, our results suggest a better candidate for the state variable. Rather than the single long-short spreading factor, our results suggest that two separated factors can better jointly work as state variables. Moreover, we expect that this analysis would provide further implication for the asset pricing studies in commodity futures markets. Vassalou (2003) constructs a factor that captures news related to the future GDP growth using equity and fixed-income portfolios, and shows that this factor subsumes the cross-sectional pricing effects of HML and SMB. In this way, if we figure out a factor which mainly drives the future GDP growth predictability of the existing factors, then it might shed light on the asset pricing test that this factor also even drives the cross-sectional pricing effects of the existing factors. We expect our findings to provide further implications in the asset pricing literature.

## References

- Bakshi, G., Gao, X., Rossi, A.G., 2017. Understanding the sources of risk underlying the cross section of commodity returns. *Management Science* 65, 619-641.
- Boons, M., Prado, M.P., 2018. Basis-momentum. *Journal of Finance* 74, 239-279.
- Carhart, M.M., 1997. On persistence in mutual fund performance. *Journal of Finance* 52, 57-82.
- Daskalaki, C., Kostakis, A., Skiadopoulos, G., 2014. Are there common factors in individual commodity futures returns? *Journal of Banking and Finance* 40, 346-363.
- Fama, E.F., French, K.R., 1989. Business conditions and expected returns on stocks. *Journal of Financial Economics* 25, 23-49.
- Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33, 3-56.
- Gorton, G.B., Hayashi, F., Rouwenhorst, K.G., 2012. The fundamentals of commodity futures returns. *Review of Finance* 17, 35-105.
- Harvey, C.R., 1989. Forecasts of economic growth from the bond and stock markets. *Financial Analyst Journal*, 38-45.
- Hong, H., Yogo, M., 2012. What does future market interest tell us about the macroeconomy and asset prices? *Journal of Financial Economics* 105, 473-490.
- Kang, J., Kim, T.S., Lee, C., Min, B., 2011, Macroeconomic risk and the cross-section of stock returns. *Journal of Banking and Finance* 35, 3158-3173.
- Kang, J., Kwon, K.Y., 2017. Momentum in international commodity futures markets. *Journal of Futures Markets* 37, 803-835.
- Kang, W., Rouwenhorst, K.G., Tang, K., 2017. A tale of two premiums: The role of hedgers and speculators in commodity futures markets. Yale International Center for Finance Working Paper No.14-24.
- Lettau, M., and Ludvigson, S., 2000. Consumption, aggregate wealth and expected stock returns. *Journal of Finance* 56, 815-849.
- Liew, J., and Vassalou, M., 2000. Can book-to-market, size, and momentum be risk factors that predict economic growth? *Journal of Financial Economics* 57, 221-245.
- Merton, R.C., 1973. An intertemporal capital asset pricing model. *Econometrica* 41, 867-887.

Miffre, J., and Rallis, G., 2007. Momentum strategies in commodity futures markets. *Journal of Banking and Finance* 31, 1863-1886.

Szymanowska, M., de Roon, R., Nijman, T., Goorbergh, R., 2014. An anatomy of commodity futures risk premia. *Journal of Finance* 69, 453-482.

Vassalou, M., 2003. News related to future GDP growth as a risk factor in equity returns. *Journal of Financial Economics* 68, 47-73.

Table 1. Summary statistics

This table presents the summary statistics (Panel A) of and correlations (Panel B) among the factors constructed by SRGN, BGR, or BP. The SRGN model includes three factors: (1) the nearby return of the High4-minus-Low4 basis portfolio ( $CR^{nb}$ ), (2) the spreading return of the High4 basis portfolio ( $CR_H^{spr}$ ), and (3) the spreading return of the Low4 basis portfolio ( $CR_L^{spr}$ ). The BGR model includes three factors: (1) the average nearby return of all sample commodity futures ( $AVG^{nb}$ ), (2) the nearby return of the High4-minus-Low4 basis portfolio as in SRGN ( $CR^{nb}$ ) and (3) the nearby return of the High4-minus-Low4 momentum portfolio ( $MOM12^{nb}$  or  $MOM6^{nb}$  depending on the ranking period of momentum, which is 12 or 6 months, respectively). The BP model includes two factors: (1) the nearby return of the High4-minus-Low4 basis-momentum portfolio ( $BM^{nb}$ ) and (2) the spreading returns of the High4-minus-Low4 basis-momentum portfolio ( $BM^{spr}$ ). Moreover,  $BM^{nb}$  ( $BM^{spr}$ ) can be further decomposed into two factors: (1) the nearby (spreading) return of the High4-minus-Low4 change in slope portfolio,  $SL^{nb}$  ( $SL^{spr}$ ), (2) the nearby (spreading) return of the High4-minus-Low4 curvature portfolio,  $CV^{nb}$  ( $CV^{spr}$ ). In addition, we also include the average spreading return of all sample commodity futures ( $AVG^{spr}$ ), the spreading return of the High4-minus-Low4 basis portfolio ( $CR^{spr}$ ), and the spreading return of the High4-minus-Low4 momentum portfolio ( $MOM12^{spr}$  or  $MOM6^{spr}$  depending on the ranking period of momentum, which is 12 or 6 months, respectively). The sample period is from 1980:1Q to 2017:4Q.

Panel A. Summary statistics						
	Mean	Standard Deviation	Skewness	Kurtosis	Minimum	Maximum
$BM^{nb}$	1.651	10.805	-0.311	0.809	-35.702	35.675
$BM^{spr}$	0.722	2.878	0.269	1.561	-7.493	11.113
$CR^{nb}$	-2.728	11.505	-0.364	0.679	-44.231	30.196
$CR^{spr}$	-0.412	3.124	-0.407	0.541	-10.818	7.886
$CR_H^{spr}$	-0.031	1.738	0.301	0.557	-5.080	4.843
$CR_L^{spr}$	0.314	2.557	0.403	1.475	-7.106	8.909
$AVG^{nb}$	0.206	6.328	-0.810	3.233	-26.344	17.196
$AVG^{spr}$	0.137	0.837	0.104	-0.182	-1.892	2.312
$MOM12^{nb}$	1.127	12.059	-0.172	0.465	-38.052	30.496
$MOM12^{spr}$	-0.142	3.048	0.138	1.407	-9.412	11.661
$MOM6^{nb}$	-0.437	13.263	-1.124	4.594	-70.516	33.305
$MOM6^{spr}$	-0.260	2.953	0.429	1.720	-8.250	11.637
$SL^{nb}$	2.798	11.364	-0.435	0.988	-39.782	33.851
$SL^{spr}$	0.056	3.043	0.211	0.999	-8.728	11.232
$CV^{nb}$	1.117	9.774	0.099	0.242	-24.970	31.605

$CV^{spr}$		0.713		2.380		0.211		0.622		-5.826		8.366			
Panel B. Correlations															
	$BM^{nb}$	$BM^{spr}$	$CR^{nb}$	$CR^{spr}$	$CR_H^{spr}$	$CR_L^{spr}$	$AVG^{nb}$	$AVG^{spr}$	$MOM12^{nb}$	$MOM12^{spr}$	$MOM6^{nb}$	$MOM6^{spr}$	$SL^{nb}$	$SL^{spr}$	$CV^{nb}$
$BM^{nb}$	1	0.440	-0.433	-0.185	-0.051	0.193	0.166	0.114	0.328	0.177	0.158	0.205	0.465	0.129	0.416
$BM^{spr}$	0.440	1	-0.308	-0.513	-0.309	0.406	0.087	0.178	0.335	0.444	0.292	0.542	0.294	0.482	0.076
$CR^{nb}$	-0.433	-0.308	1	0.475	0.347	-0.334	-0.085	-0.061	-0.330	-0.231	-0.281	-0.288	-0.608	-0.238	-0.052
$CR^{spr}$	-0.185	-0.513	0.475	1	0.549	-0.828	0.011	-0.258	-0.213	-0.438	-0.184	-0.428	-0.226	-0.397	0.006
$CR_H^{spr}$	-0.051	-0.309	0.347	0.549	1	0.013	-0.012	0.490	-0.182	-0.264	-0.181	-0.217	-0.168	-0.334	0.059
$CR_L^{spr}$	0.193	0.406	-0.334	-0.828	0.013	1	-0.018	0.635	0.134	0.344	0.103	0.371	0.157	0.258	0.037
$AVG^{nb}$	0.166	0.087	-0.085	0.011	-0.012	-0.018	1	0.046	0.238	0.159	0.078	0.087	0.101	0.190	0.128
$AVG^{spr}$	0.114	0.178	-0.061	-0.258	0.490	0.635	0.046	1	0.010	0.234	-0.037	0.244	0.069	0.060	0.079
$MOM12^{nb}$	0.328	0.335	-0.330	-0.213	-0.182	0.134	0.238	0.010	1	0.512	0.443	0.370	0.339	0.185	0.185
$MOM12^{spr}$	0.177	0.444	-0.231	-0.438	-0.264	0.344	0.159	0.234	0.512	1	0.272	0.707	0.213	0.427	0.007
$MOM6^{nb}$	0.158	0.292	-0.281	-0.184	-0.181	0.103	0.078	-0.037	0.443	0.272	1	0.451	0.142	0.167	-0.057
$MOM6^{spr}$	0.205	0.542	-0.288	-0.428	-0.217	0.371	0.087	0.244	0.370	0.707	0.451	1	0.257	0.439	0.004
$SL^{nb}$	0.465	0.294	-0.608	-0.226	-0.168	0.157	0.101	0.069	0.339	0.213	0.142	0.257	1	0.391	-0.031
$SL^{spr}$	0.129	0.482	-0.238	-0.397	-0.334	0.258	0.190	0.060	0.185	0.427	0.167	0.439	0.391	1	-0.115
$CV^{nb}$	0.416	0.076	-0.052	0.006	0.059	0.037	0.128	0.079	0.185	0.007	-0.057	0.004	-0.031	-0.115	1
$CV^{spr}$	0.191	0.392	-0.185	-0.205	-0.119	0.162	0.078	0.144	0.214	0.240	0.026	0.208	0.149	-0.012	0.391

Table 2. Univariate regression

This table presents the results from the univariate predictive regressions. In Eq. (1),  $F_t$  is each individual commodity futures risk factors denoted on the left most column and no controlling variables ( $C_t$ ). The dependent variable is  $GDP\ growth_{t+1Q,t+hQ}$  which is the GDP growth for future  $h$  quarters from quarter  $t+1Q$  to quarter  $t+hQ$  for  $h = 1$  to 8. For each regression, we report the coefficient on the commodity futures risk factor, its t-statistics which is the number in parentheses, and the adjusted  $R^2$  value of the regression. The t-statistics are computed using the Newey and West (1987) method with  $2h+1$  lags. The sample period is from 1980:1Q to 2017:4Q.

Variable		Horizon ( $h$ )							
		1	2	3	4	5	6	7	8
$BM^{nb}$	Coefficient	0.029	0.010	0.005	-0.001	-0.002	-0.006	-0.008	-0.006
	(t-stat)	(1.71)	(0.78)	(0.45)	(-0.07)	(-0.25)	(-0.72)	(-0.92)	(-0.75)
	adj. $R^2$	2.15%	-0.16%	-0.54%	-0.67%	-0.64%	-0.40%	-0.18%	-0.31%
$BM^{spr}$	Coefficient	0.034	-0.023	-0.042	-0.062	-0.071	-0.071	-0.068	-0.062
	(t-stat)	(0.55)	(-0.44)	(-1.10)	(-2.08)	(-2.64)	(-2.70)	(-2.63)	(-2.47)
	adj. $R^2$	-0.38%	-0.49%	0.06%	1.14%	1.79%	2.09%	2.16%	1.87%
$CR^{nb}$	Coefficient	-0.013	0.001	0.005	0.006	0.006	0.006	0.006	0.005
	(t-stat)	(-1.06)	(0.09)	(0.46)	(0.49)	(0.49)	(0.54)	(0.62)	(0.60)
	adj. $R^2$	0.05%	-0.66%	-0.49%	-0.43%	-0.43%	-0.39%	-0.36%	-0.42%
$CR^{spr}$	Coefficient	-0.024	0.009	0.023	0.032	0.033	0.030	0.026	0.023
	(t-stat)	(-0.48)	(0.24)	(0.75)	(1.11)	(1.14)	(1.12)	(1.02)	(0.89)
	adj. $R^2$	-0.50%	-0.63%	-0.41%	-0.09%	-0.04%	-0.09%	-0.19%	-0.26%
$CR_H^{spr}$	Coefficient	0.025	0.032	0.049	0.072	0.107	0.120	0.118	0.120
	(t-stat)	(0.37)	(0.57)	(0.92)	(1.15)	(1.67)	(2.09)	(2.35)	(2.59)
	adj. $R^2$	-0.61%	-0.54%	-0.31%	0.21%	1.43%	2.26%	2.48%	2.90%
$CR_L^{spr}$	Coefficient	0.049	0.002	-0.012	-0.015	0.001	0.011	0.016	0.022
	(t-stat)	(0.61)	(0.04)	(-0.26)	(-0.36)	(0.02)	(0.26)	(0.39)	(0.53)
	adj. $R^2$	-0.21%	-0.67%	-0.62%	-0.58%	-0.68%	-0.63%	-0.55%	-0.42%
$AVG^{nb}$	Coefficient	0.091	0.064	0.049	0.041	0.037	0.026	0.022	0.017
	(t-stat)	(2.11)	(1.87)	(2.01)	(1.95)	(1.85)	(1.43)	(1.32)	(1.18)

	adj. $R^2$	9.07%	6.14%	4.07%	3.03%	2.69%	1.24%	0.73%	0.26%
$AVG^{spr}$	Coefficient	0.143	-0.057	-0.062	-0.008	0.068	0.101	0.098	0.121
	(t-stat)	(0.66)	(-0.37)	(-0.44)	(-0.05)	(0.43)	(0.69)	(0.73)	(0.92)
	adj. $R^2$	-0.24%	-0.57%	-0.53%	-0.67%	-0.47%	-0.19%	-0.17%	0.16%
$MOM12^{nb}$	Coefficient	0.006	-0.004	-0.007	-0.011	-0.014	-0.015	-0.012	-0.010
	(t-stat)	(0.32)	(-0.32)	(-0.67)	(-1.28)	(-1.59)	(-1.94)	(-1.88)	(-1.66)
	adj. $R^2$	-0.52%	-0.55%	-0.32%	0.38%	0.99%	1.41%	0.98%	0.44%
$MOM12^{spr}$	Coefficient	0.016	-0.021	-0.027	-0.031	-0.027	-0.017	-0.009	-0.005
	(t-stat)	(0.26)	(-0.44)	(-0.78)	(-1.13)	(-0.98)	(-0.60)	(-0.33)	(-0.17)
	adj. $R^2$	-0.59%	-0.50%	-0.32%	-0.15%	-0.27%	-0.51%	-0.63%	-0.67%
$MOM6^{nb}$	Coefficient	0.007	0.005	0.002	-0.001	-0.004	-0.006	-0.005	-0.003
	(t-stat)	(0.59)	(0.48)	(0.29)	(-0.15)	(-0.53)	(-0.82)	(-0.83)	(-0.60)
	adj. $R^2$	-0.44%	-0.47%	-0.61%	-0.66%	-0.51%	-0.34%	-0.43%	-0.60%
$MOM6^{spr}$	Coefficient	0.018	-0.020	-0.018	-0.026	-0.024	-0.014	-0.006	0.003
	(t-stat)	(0.29)	(-0.41)	(-0.47)	(-0.84)	(-0.78)	(-0.45)	(-0.19)	(0.07)
	adj. $R^2$	-0.58%	-0.53%	-0.52%	-0.35%	-0.38%	-0.56%	-0.66%	-0.69%
$SL^{nb}$	Coefficient	0.007	-0.005	-0.006	-0.008	-0.009	-0.008	-0.007	-0.004
	(t-stat)	(0.67)	(-0.55)	(-0.76)	(-0.88)	(-0.78)	(-0.67)	(-0.64)	(-0.42)
	adj. $R^2$	-0.45%	-0.53%	-0.42%	-0.16%	-0.09%	-0.15%	-0.19%	-0.50%
$SL^{spr}$	Coefficient	-0.036	-0.061	-0.062	-0.084	-0.087	-0.087	-0.088	-0.076
	(t-stat)	(-0.75)	(-1.61)	(-1.97)	(-2.83)	(-2.89)	(-3.07)	(-3.69)	(-3.79)
	adj. $R^2$	-0.24%	0.87%	1.14%	3.05%	3.73%	4.05%	4.64%	3.69%
$CV^{nb}$	Coefficient	0.007	0.003	-0.002	-0.005	-0.004	-0.003	-0.003	-0.002
	(t-stat)	(0.37)	(0.19)	(-0.16)	(-0.46)	(-0.44)	(-0.37)	(-0.30)	(-0.29)
	adj. $R^2$	-0.52%	-0.64%	-0.65%	-0.55%	-0.56%	-0.61%	-0.64%	-0.65%
$CV^{spr}$	Coefficient	0.036	0.000	-0.039	-0.045	-0.037	-0.025	-0.021	-0.023
	(t-stat)	(0.51)	(0.01)	(-0.77)	(-1.00)	(-0.89)	(-0.60)	(-0.53)	(-0.57)
	adj. $R^2$	-0.42%	-0.67%	-0.25%	-0.02%	-0.19%	-0.44%	-0.49%	-0.45%

Table 3. Multivariate regression

This table presents the results from the multivariate predictive regressions. In Eq. (1),  $F_t$  is a set of commodity futures risk factors for each model and no controlling variables ( $C_t$ ). The dependent variable is  $GDP\ growth_{t+1Q,t+hQ}$  which is the GDP growth for future  $h$  quarters from quarter  $t+1Q$  to quarter  $t+hQ$  for  $h = 1$  to 8. For each regression, we report the coefficient on the commodity futures risk factor, its t-statistics which is the number in parentheses, and the adjusted  $R^2$  value of the regression. The t-statistics are computed using the Newey and West (1987) method with  $2h+1$  lags. The sample period is from 1980:1Q to 2017:4Q.

Model	Variable		Horizon ( $h$ )							
			1	2	3	4	5	6	7	8
1	$BM^{nb}$	Coefficient	0.030	0.016	0.012	0.008	0.007	0.003	0.000	0.001
		(t-stat)	(1.93)	(1.39)	(1.18)	(0.92)	(0.83)	(0.37)	(0.04)	(0.11)
	$BM^{spr}$	Coefficient	-0.016	-0.049	-0.061	-0.076	-0.082	-0.076	-0.069	-0.064
		(t-stat)	(-0.27)	(-1.02)	(-1.62)	(-2.49)	(-3.11)	(-3.00)	(-2.71)	(-2.55)
		adj. $R^2$	1.54%	-0.16%	0.05%	0.85%	1.42%	1.47%	1.48%	1.20%
	2	$AVG^{nb}$	Coefficient	0.085	0.063	0.049	0.042	0.039	0.030	0.025
(t-stat)			(2.13)	(1.86)	(1.98)	(2.00)	(2.02)	(1.70)	(1.73)	(1.59)
$BM^{nb}$		Coefficient	0.022	0.010	0.007	0.004	0.003	0.000	-0.002	-0.001
		(t-stat)	(1.82)	(0.98)	(0.70)	(0.45)	(0.41)	(0.00)	(-0.27)	(-0.11)
$BM^{spr}$		Coefficient	-0.019	-0.052	-0.063	-0.078	-0.085	-0.078	-0.071	-0.065
		(t-stat)	(-0.33)	(-1.08)	(-1.69)	(-2.54)	(-3.22)	(-3.02)	(-2.76)	(-2.58)
	adj. $R^2$	9.32%	5.70%	4.12%	4.16%	4.56%	3.19%	2.70%	1.80%	
3	$CR^{nb}$	Coefficient	-0.015	-0.001	0.002	0.001	0.000	0.000	0.001	0.000
		(t-stat)	(-1.14)	(-0.05)	(0.19)	(0.08)	(-0.01)	(0.00)	(0.07)	(0.02)
	$CR_H^{spr}$	Coefficient	0.058	0.033	0.044	0.070	0.107	0.120	0.116	0.118
		(t-stat)	(0.77)	(0.55)	(0.84)	(1.34)	(2.11)	(2.56)	(2.72)	(2.88)
	$CR_L^{spr}$	Coefficient	0.026	0.001	-0.009	-0.014	-0.001	0.009	0.015	0.020
		(t-stat)	(0.34)	(0.02)	(-0.19)	(-0.31)	(-0.02)	(0.18)	(0.33)	(0.45)
	adj. $R^2$	-0.86%	-1.89%	-1.59%	-1.04%	0.08%	0.95%	1.23%	1.75%	
4	$AVG^{nb}$	Coefficient	0.093	0.070	0.055	0.048	0.046	0.035	0.029	0.023

		(t-stat)	(2.21)	(2.03)	(2.18)	(2.29)	(2.38)	(2.01)	(1.94)	(1.75)
	$CR^{nb}$	Coefficient	-0.013	0.000	0.003	0.002	0.001	0.001	0.002	0.001
		(t-stat)	(-0.98)	(-0.01)	(0.26)	(0.18)	(0.10)	(0.08)	(0.20)	(0.17)
	$MOM12^{nb}$	Coefficient	-0.010	-0.013	-0.013	-0.017	-0.019	-0.019	-0.016	-0.013
		(t-stat)	(-0.75)	(-1.18)	(-1.31)	(-2.05)	(-2.39)	(-2.63)	(-2.58)	(-2.29)
		adj. $R^2$	8.54%	5.86%	4.16%	4.11%	4.61%	3.31%	2.07%	0.76%
5	$AVG^{nb}$	Coefficient	0.089	0.064	0.050	0.042	0.038	0.028	0.023	0.018
		(t-stat)	(2.09)	(1.82)	(1.93)	(1.91)	(1.89)	(1.50)	(1.44)	(1.26)
	$CR^{nb}$	Coefficient	-0.009	0.005	0.008	0.007	0.006	0.005	0.005	0.005
		(t-stat)	(-0.78)	(0.49)	(0.75)	(0.65)	(0.56)	(0.52)	(0.60)	(0.60)
	$MOM6^{nb}$	Coefficient	0.001	0.004	0.003	-0.001	-0.004	-0.005	-0.004	-0.002
		(t-stat)	(0.09)	(0.36)	(0.29)	(-0.11)	(-0.54)	(-0.81)	(-0.79)	(-0.48)
		adj. $R^2$	8.19%	5.08%	3.21%	2.16%	1.96%	0.62%	0.01%	-0.71%
6	$SL^{nb}$	Coefficient	0.012	0.002	0.002	0.002	0.002	0.002	0.003	0.005
		(t-stat)	(1.36)	(0.23)	(0.24)	(0.24)	(0.19)	(0.22)	(0.32)	(0.56)
	$SL^{spr}$	Coefficient	-0.052	-0.064	-0.065	-0.089	-0.092	-0.092	-0.095	-0.086
		(t-stat)	(-1.03)	(-1.60)	(-1.94)	(-3.05)	(-3.18)	(-3.49)	(-3.95)	(-3.99)
	$CV^{nb}$	Coefficient	0.003	0.001	0.000	-0.004	-0.005	-0.005	-0.005	-0.004
		(t-stat)	(0.18)	(0.06)	(-0.03)	(-0.38)	(-0.44)	(-0.55)	(-0.52)	(-0.46)
	$CV^{spr}$	Coefficient	0.021	-0.003	-0.040	-0.042	-0.032	-0.021	-0.017	-0.023
		(t-stat)	(0.34)	(-0.06)	(-0.84)	(-1.02)	(-0.90)	(-0.57)	(-0.50)	(-0.66)
		adj. $R^2$	-1.50%	-1.15%	-0.42%	1.86%	2.39%	2.52%	3.09%	2.33%
7	$AVG^{nb}$	Coefficient	0.074	0.062	0.054	0.050	0.047	0.035	0.030	0.022
		(t-stat)	(1.77)	(1.69)	(2.01)	(2.24)	(2.33)	(1.98)	(2.12)	(1.93)
	$SL^{nb}$	Coefficient	0.011	0.001	0.001	0.002	0.001	0.002	0.003	0.005
		(t-stat)	(1.22)	(0.12)	(0.14)	(0.17)	(0.14)	(0.17)	(0.29)	(0.53)
	$SL^{spr}$	Coefficient	-0.082	-0.088	-0.087	-0.110	-0.111	-0.107	-0.107	-0.095
		(t-stat)	(-1.74)	(-2.44)	(-2.68)	(-3.61)	(-3.70)	(-3.82)	(-4.36)	(-4.41)
	$CV^{nb}$	Coefficient	-0.003	-0.005	-0.005	-0.009	-0.009	-0.008	-0.008	-0.006

	(t-stat)	(-0.23)	(-0.34)	(-0.44)	(-0.79)	(-0.89)	(-0.97)	(-0.89)	(-0.76)
$CV^{spr}$	Coefficient	0.017	-0.007	-0.043	-0.044	-0.035	-0.023	-0.019	-0.024
	(t-stat)	(0.28)	(-0.12)	(-0.86)	(-1.02)	(-0.91)	(-0.59)	(-0.52)	(-0.67)
	adj. $R^2$	4.91%	4.39%	4.38%	6.50%	6.77%	5.00%	4.94%	3.17%

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Table 4. Correlations with control variables

This table presents correlations among commodity futures risk factors and other control variables. For macroeconomic variables, we include the short-term interest rate (TB), term spread (TERM), default spread (DEF), and the variable CAY suggested by Lettau and Ludvigson (2000). In specific, we use the three-month Treasury bill rate for TB, the yield spread between 10-year government bonds and 1-year government bonds for TERM, and the yield spread between Moody's BAA and AAA corporate bonds for DEF. CAY is a detrended wealth variable. For equity risk factors, we employ Fama and French's (1993) three-factor model, which includes the market factor (RMRF), the size factor (SMB), and the value factor (HML). The sample period is from 1982:1Q to 2017:3Q.

	RMRF	SMB	HML	TB	DEF	TERM	CAY
RMRF	1	0.444	-0.133	-0.018	-0.213	-0.001	-0.126
SMB	0.444	1	0.018	-0.105	0.114	0.213	-0.073
HML	-0.133	0.018	1	0.010	-0.043	0.227	0.064
TB	-0.018	-0.105	0.010	1	-0.464	-0.322	0.546
DEF	-0.213	0.114	-0.043	-0.464	1	0.276	-0.266
TERM	-0.001	0.213	0.227	-0.322	0.276	1	-0.013
CAY	-0.126	-0.073	0.064	0.546	-0.266	-0.013	1
<i>BM<sup>nb</sup></i>	-0.051	0.019	0.008	0.196	-0.214	-0.009	0.046
<i>BM<sup>spr</sup></i>	-0.031	0.020	-0.098	0.114	0.005	-0.002	-0.062
<i>CR<sup>nb</sup></i>	0.031	-0.088	-0.120	0.033	-0.037	-0.099	0.142
<i>CR<sup>spr</sup></i>	-0.025	-0.059	-0.030	0.064	-0.152	-0.040	0.079
<i>CR<sub>H</sub><sup>spr</sup></i>	-0.012	-0.065	0.012	-0.061	-0.063	-0.026	-0.057
<i>CR<sub>L</sub><sup>spr</sup></i>	0.022	0.030	0.047	-0.113	0.139	0.031	-0.130
<i>AVG<sup>nb</sup></i>	0.215	0.117	0.046	-0.037	-0.191	0.108	-0.056
<i>AVG<sup>spr</sup></i>	0.024	-0.061	0.001	-0.036	0.067	-0.046	-0.086
<i>MOM12<sup>nb</sup></i>	0.045	0.038	-0.028	0.140	-0.195	0.021	0.082
<i>MOM12<sup>spr</sup></i>	0.066	0.065	-0.024	0.166	0.034	0.005	0.029
<i>MOM6<sup>nb</sup></i>	0.098	0.080	-0.082	0.062	-0.026	0.002	0.035
<i>MOM6<sup>spr</sup></i>	0.135	0.143	-0.077	0.118	0.067	-0.019	-0.009
<i>SL<sup>nb</sup></i>	0.021	0.024	0.016	0.043	-0.018	-0.063	0.002
<i>SL<sup>spr</sup></i>	0.088	0.045	-0.047	0.062	0.072	-0.053	-0.024
<i>CV<sup>nb</sup></i>	-0.108	-0.068	-0.009	0.159	-0.178	0.018	0.097
<i>CV<sup>spr</sup></i>	-0.015	0.063	-0.049	0.063	0.000	0.070	-0.128

Table 5. Predictability after controlling for macroeconomic variables

This table presents the predictive regressions including macroeconomic variables. In Eq. (1),  $F_t$  is each individual commodity futures risk factors and  $C_t$  is a set of controlling variables, either a set of macroeconomic variables or a set of equity risk factors. For macroeconomic variables, we include the short-term interest rate (TB), term spread (TERM), default spread (DEF), and the variable CAY suggested by Lettau and Ludvigson (2000). In specific, we use the three-month Treasury bill rate for TB, the yield spread between 10-year government bonds and 1-year government bonds for TERM, and the yield spread between Moody's BAA and AAA corporate bonds for DEF. CAY is a detrended wealth variable. The dependent variable is  $GDP\ growth_{t+1Q,t+hQ}$  which is the GDP growth for future  $h$  quarters from quarter  $t+1Q$  to quarter  $t+hQ$  for  $h = 1$  to 8. For each regression, we report the coefficient on the commodity futures risk factor, its t-statistics which is the number in parentheses, and the adjusted  $R^2$  value of the regression. The t-statistics are computed using the Newey and West (1987) method with  $2h+1$  lags. The sample period is from 1982:1Q to 2017:3Q.

Panel A. Predictability of macroeconomic variables									
Variable		Horizon ( $h$ )							
		1	2	3	4	5	6	7	8
TB	Coefficient	0.0004	0.050	0.051	0.055	0.057	0.054	0.049	0.042
	(t-stat)	(0.51)	(0.61)	(0.68)	(0.80)	(0.86)	(0.83)	(0.77)	(0.69)
	adj. $R^2$	-0.08%	0.39%	0.64%	1.09%	1.44%	1.40%	1.20%	0.93%
DEF	Coefficient	-0.010	-0.788	-0.600	-0.488	-0.370	-0.256	-0.190	-0.148
	(t-stat)	(-3.15)	(-2.63)	(-2.12)	(-1.84)	(-1.49)	(-1.08)	(-0.82)	(-0.63)
	adj. $R^2$	17.94%	13.75%	9.13%	6.76%	4.10%	1.81%	0.84%	0.33%
TERM	Coefficient	0.001	0.110	0.155	0.198	0.224	0.251	0.271	0.270
	(t-stat)	(0.64)	(0.62)	(0.84)	(1.08)	(1.22)	(1.32)	(1.42)	(1.48)
	adj. $R^2$	-0.34%	-0.21%	0.50%	1.58%	2.58%	3.87%	5.28%	6.09%
CAY	Coefficient	0.044	5.676	5.967	5.765	6.226	7.126	8.467	8.567
	(t-stat)	(0.56)	(0.71)	(0.75)	(0.74)	(0.76)	(0.79)	(0.86)	(0.84)
	adj. $R^2$	-0.53%	-0.28%	-0.14%	-0.10%	0.08%	0.42%	1.06%	1.33%
TB	Coefficient	-0.0004	-0.010	0.018	0.045	0.064	0.072	0.067	0.060
	(t-stat)	(-0.38)	(-0.09)	(0.17)	(0.45)	(0.63)	(0.70)	(0.65)	(0.60)
DEF	Coefficient	-0.012	-0.938	-0.703	-0.560	-0.405	-0.266	-0.191	-0.147
	(t-stat)	(-3.67)	(-2.92)	(-2.33)	(-1.92)	(-1.42)	(-0.93)	(-0.66)	(-0.51)

TERM	Coefficient	0.003	0.288	0.315	0.356	0.371	0.380	0.381	0.365
	(t-stat)	(1.82)	(1.58)	(1.58)	(1.72)	(1.72)	(1.71)	(1.73)	(1.74)
CAY	Coefficient	-0.046	-3.206	-3.092	-4.327	-3.973	-2.119	0.565	1.790
	(t-stat)	(-0.39)	(-0.28)	(-0.30)	(-0.43)	(-0.36)	(-0.18)	(0.04)	(0.13)
	adj. $R^2$	20.81%	15.53%	11.53%	11.07%	10.00%	9.36%	10.12%	10.41%

Panel B. Univariate regression controlling for macroeconomic variables

Variable	Horizon ( $h$ )								
		1	2	3	4	5	6	7	8
$BM^{nb}$	Coefficient	0.0001	0.001	-0.002	-0.005	-0.006	-0.009	-0.010	-0.008
	(t-stat)	(1.18)	(0.14)	(-0.17)	(-0.51)	(-0.65)	(-1.06)	(-1.36)	(-1.26)
	adj. $R^2$	20.77%	14.89%	10.87%	10.60%	9.59%	9.39%	10.40%	10.44%
$BM^{spr}$	Coefficient	0.0004	-0.003	-0.027	-0.052	-0.063	-0.067	-0.066	-0.063
	(t-stat)	(0.71)	(-0.07)	(-0.70)	(-1.47)	(-1.74)	(-2.09)	(-2.36)	(-2.58)
	adj. $R^2$	20.62%	14.88%	11.15%	11.69%	11.28%	11.17%	12.17%	12.52%
$CR^{nb}$	Coefficient	0.0000	0.005	0.009	0.010	0.012	0.012	0.011	0.011
	(t-stat)	(-0.33)	(0.44)	(0.67)	(0.74)	(0.87)	(0.97)	(1.16)	(1.23)
	adj. $R^2$	20.26%	15.02%	11.33%	11.15%	10.43%	9.87%	10.73%	11.05%
$CR^{spr}$	Coefficient	-0.0002	-0.002	0.008	0.022	0.029	0.032	0.030	0.032
	(t-stat)	(-0.59)	(-0.09)	(0.31)	(0.83)	(1.08)	(1.21)	(1.15)	(1.22)
	adj. $R^2$	20.33%	14.88%	10.89%	10.68%	9.87%	9.39%	10.15%	10.65%
$CR_H^{spr}$	Coefficient	-0.0002	-0.013	0.016	0.043	0.082	0.095	0.090	0.090
	(t-stat)	(-0.27)	(-0.27)	(0.34)	(0.75)	(1.34)	(1.68)	(1.89)	(2.05)
	adj. $R^2$	20.24%	14.91%	10.89%	10.75%	10.76%	10.81%	11.59%	12.16%
$CR_L^{spr}$	Coefficient	0.0002	-0.005	-0.007	-0.015	-0.006	-0.002	-0.001	-0.004
	(t-stat)	(0.37)	(-0.12)	(-0.16)	(-0.34)	(-0.12)	(-0.04)	(-0.03)	(-0.09)
	adj. $R^2$	20.27%	14.89%	10.87%	10.47%	9.31%	8.66%	9.41%	9.70%
$AVG^{nb}$	Coefficient	0.0003	0.018	0.012	0.007	0.006	-0.001	-0.001	-0.002
	(t-stat)	(0.87)	(0.59)	(0.54)	(0.35)	(0.33)	(-0.05)	(-0.06)	(-0.13)
	adj. $R^2$	21.22%	15.41%	11.14%	10.50%	9.40%	8.66%	9.42%	9.71%

<i>AVG<sup>spr</sup></i>	Coefficient	0.0001	-0.110	-0.086	-0.028	0.045	0.061	0.046	0.052
	(t-stat)	(0.05)	(-0.79)	(-0.57)	(-0.17)	(0.26)	(0.39)	(0.33)	(0.41)
	adj. $R^2$	20.21%	15.24%	11.11%	10.42%	9.39%	8.84%	9.53%	9.87%
<i>MOM12<sup>nb</sup></i>	Coefficient	-0.0001	-0.016	-0.016	-0.018	-0.019	-0.018	-0.015	-0.011
	(t-stat)	(-1.14)	(-1.86)	(-1.64)	(-1.79)	(-1.78)	(-1.93)	(-1.78)	(-1.46)
	adj. $R^2$	20.96%	16.59%	12.65%	13.32%	12.69%	12.04%	11.94%	11.20%
<i>MOM12<sup>spr</sup></i>	Coefficient	0.0000	-0.019	-0.021	-0.024	-0.017	-0.010	-0.003	-0.0004
	(t-stat)	(-0.07)	(-0.48)	(-0.57)	(-0.74)	(-0.55)	(-0.37)	(-0.12)	(-0.02)
	adj. $R^2$	20.21%	15.02%	11.04%	10.68%	9.46%	8.71%	9.42%	9.69%
<i>MOM6<sup>nb</sup></i>	Coefficient	0.0000	0.004	0.003	0.0002	-0.002	-0.003	-0.002	-0.0006
	(t-stat)	(0.03)	(0.32)	(0.28)	(0.01)	(-0.15)	(-0.33)	(-0.31)	(-0.09)
	adj. $R^2$	20.21%	15.02%	10.95%	10.39%	9.33%	8.78%	9.49%	9.70%
<i>MOM6<sup>spr</sup></i>	Coefficient	0.0001	-0.007	0.000	-0.009	-0.008	-0.005	-0.002	0.001
	(t-stat)	(0.23)	(-0.13)	(0.00)	(-0.23)	(-0.20)	(-0.16)	(-0.07)	(0.05)
	adj. $R^2$	20.24%	14.90%	10.85%	10.43%	9.33%	8.67%	9.42%	9.70%
<i>SL<sup>nb</sup></i>	Coefficient	0.0001	-0.002	-0.003	-0.007	-0.009	-0.009	-0.009	-0.006
	(t-stat)	(0.70)	(-0.20)	(-0.37)	(-0.73)	(-0.80)	(-0.76)	(-0.84)	(-0.57)
	adj. $R^2$	20.40%	14.90%	10.92%	10.78%	9.98%	9.38%	10.20%	10.05%
<i>SL<sup>spr</sup></i>	Coefficient	-0.0002	-0.033	-0.038	-0.063	-0.066	-0.070	-0.074	-0.065
	(t-stat)	(-0.44)	(-0.75)	(-0.96)	(-1.62)	(-1.62)	(-1.79)	(-2.20)	(-2.09)
	adj. $R^2$	20.37%	15.33%	11.53%	12.52%	11.96%	11.92%	13.51%	13.26%
<i>CV<sup>nb</sup></i>	Coefficient	0.0000	-0.006	-0.013	-0.015	-0.015	-0.012	-0.011	-0.011
	(t-stat)	(-0.21)	(-0.43)	(-1.04)	(-1.34)	(-1.37)	(-1.33)	(-1.38)	(-1.54)
	adj. $R^2$	20.23%	15.02%	11.62%	11.68%	10.64%	9.67%	10.30%	10.72%
<i>CV<sup>spr</sup></i>	Coefficient	0.0004	0.011	-0.037	-0.052	-0.047	-0.035	-0.032	-0.036
	(t-stat)	(0.77)	(0.23)	(-0.86)	(-1.23)	(-1.17)	(-0.93)	(-0.98)	(-1.27)
	adj. $R^2$	20.53%	14.91%	11.27%	11.34%	10.17%	9.17%	9.90%	10.40%

Table 6. Predictability after controlling for equity risk factors

This table presents the predictive regressions including macroeconomic variables. In Eq. (1),  $F_t$  is each individual commodity futures risk factors and  $C_t$  a set of equity risk factors. For equity risk factors, we employ Fama and French's (1993) three-factor model, which includes the market factor (RMRF), the size factor (SMB), and the value factor (HML). The dependent variable is  $GDP\ growth_{t+1Q,t+hQ}$  which is the GDP growth for future  $h$  quarters from quarter  $t+1Q$  to quarter  $t+hQ$  for  $h = 1$  to 8. For each regression, we report the coefficient on the commodity futures risk factor, its t-statistics which is the number in parentheses, and the adjusted  $R^2$  value of the regression. The t-statistics are computed using the Newey and West (1987) method with  $2h+1$  lags. The sample period is from 1982:1Q to 2017:3Q.

Panel A. Predictability of equity risk factors									
Variable		Horizon ( $h$ )							
		1	2	3	4	5	6	7	8
RMRF	Coefficient	0.0007	0.065	0.058	0.053	0.048	0.042	0.034	0.030
	(t-stat)	(2.69)	(2.76)	(2.75)	(2.51)	(2.56)	(2.75)	(2.58)	(2.50)
	adj. $R^2$	11.28%	12.29%	11.68%	10.97%	10.22%	8.31%	5.95%	5.20%
SMB	Coefficient	0.0002	0.008	0.011	0.014	0.022	0.020	0.017	0.016
	(t-stat)	(0.65)	(0.25)	(0.36)	(0.46)	(0.72)	(0.66)	(0.57)	(0.57)
	adj. $R^2$	-0.33%	-0.67%	-0.59%	-0.49%	-0.03%	-0.10%	-0.24%	-0.23%
HML	Coefficient	0.0002	0.005	0.014	0.018	0.020	0.023	0.026	0.025
	(t-stat)	(0.67)	(0.23)	(0.61)	(0.84)	(0.98)	(1.23)	(1.57)	(1.79)
	adj. $R^2$	-0.24%	-0.68%	-0.28%	0.22%	0.58%	1.19%	1.99%	1.89%
RMRF	Coefficient	0.0009	0.081	0.073	0.066	0.057	0.050	0.041	0.037
	(t-stat)	(2.68)	(2.76)	(2.82)	(2.66)	(2.59)	(2.74)	(2.56)	(2.43)
	adj. $R^2$	12.61%	13.99%	13.75%	13.38%	12.19%	10.79%	9.02%	8.06%
SMB	Coefficient	-0.0004	-0.055	-0.046	-0.038	-0.024	-0.020	-0.017	-0.014
	(t-stat)	(-0.98)	(-1.30)	(-1.22)	(-1.14)	(-0.75)	(-0.65)	(-0.53)	(-0.45)
	adj. $R^2$								
HML	Coefficient	0.0003	0.019	0.026	0.030	0.030	0.032	0.033	0.031
	(t-stat)	(1.28)	(0.90)	(1.27)	(1.57)	(1.65)	(1.93)	(2.26)	(2.65)
	adj. $R^2$								

  

Panel B. Univariate regression controlling for equity risk factors									
Variable		Horizon ( $h$ )							
		1	2	3	4	5	6	7	8
RMRF	Coefficient	0.0009	0.081	0.073	0.066	0.057	0.050	0.041	0.037
	(t-stat)	(2.68)	(2.76)	(2.82)	(2.66)	(2.59)	(2.74)	(2.56)	(2.43)
	adj. $R^2$	12.61%	13.99%	13.75%	13.38%	12.19%	10.79%	9.02%	8.06%
SMB	Coefficient	-0.0004	-0.055	-0.046	-0.038	-0.024	-0.020	-0.017	-0.014
	(t-stat)	(-0.98)	(-1.30)	(-1.22)	(-1.14)	(-0.75)	(-0.65)	(-0.53)	(-0.45)
	adj. $R^2$								
HML	Coefficient	0.0003	0.019	0.026	0.030	0.030	0.032	0.033	0.031
	(t-stat)	(1.28)	(0.90)	(1.27)	(1.57)	(1.65)	(1.93)	(2.26)	(2.65)
	adj. $R^2$								

		1	2	3	4	5	6	7	8
$BM^{nb}$	Coefficient	0.0003	0.017	0.012	0.008	0.005	0.001	-0.002	-0.0004
	(t-stat)	(2.16)	(1.59)	(1.37)	(0.88)	(0.66)	(0.10)	(-0.23)	(-0.06)
	adj. $R^2$	15.60%	14.90%	14.03%	13.14%	11.74%	10.10%	8.34%	7.33%
$BM^{spr}$	Coefficient	0.0005	0.010	-0.009	-0.030	-0.039	-0.044	-0.047	-0.044
	(t-stat)	(0.81)	(0.19)	(-0.25)	(-0.94)	(-1.39)	(-1.69)	(-1.91)	(-1.99)
	adj. $R^2$	12.62%	13.36%	13.13%	13.14%	12.31%	11.23%	9.73%	8.75%
$CR^{nb}$	Coefficient	-0.0001	0.001	0.005	0.007	0.009	0.009	0.010	0.009
	(t-stat)	(-0.56)	(0.13)	(0.49)	(0.54)	(0.73)	(0.83)	(1.07)	(1.10)
	adj. $R^2$	12.09%	13.34%	13.28%	13.07%	12.19%	10.90%	9.36%	8.34%
$CR^{spr}$	Coefficient	0.0002	0.026	0.030	0.040	0.046	0.046	0.043	0.041
	(t-stat)	(0.53)	(0.82)	(1.04)	(1.41)	(1.69)	(1.84)	(1.89)	(1.82)
	adj. $R^2$	12.09%	13.64%	13.59%	13.72%	12.93%	11.66%	9.83%	8.91%
$CR_H^{spr}$	Coefficient	0.0001	0.004	0.024	0.045	0.081	0.091	0.084	0.082
	(t-stat)	(0.23)	(0.08)	(0.47)	(0.72)	(1.21)	(1.44)	(1.51)	(1.68)
	adj. $R^2$	11.96%	13.33%	13.19%	13.11%	12.94%	12.05%	10.17%	9.39%
$CR_L^{spr}$	Coefficient	-0.0003	-0.040	-0.037	-0.041	-0.031	-0.026	-0.024	-0.021
	(t-stat)	(-0.55)	(-0.94)	(-0.92)	(-1.10)	(-0.87)	(-0.76)	(-0.72)	(-0.66)
	adj. $R^2$	12.11%	13.79%	13.56%	13.38%	11.93%	10.41%	8.62%	7.60%
$AVG^{nb}$	Coefficient	0.0004	0.025	0.015	0.008	0.005	-0.004	-0.004	-0.004
	(t-stat)	(1.05)	(0.78)	(0.70)	(0.48)	(0.33)	(-0.26)	(-0.27)	(-0.38)
	adj. $R^2$	14.08%	14.36%	13.53%	12.87%	11.59%	10.14%	8.35%	7.39%
$AVG^{spr}$	Coefficient	-0.0011	-0.215	-0.178	-0.111	-0.028	-0.006	-0.017	0.004
	(t-stat)	(-0.84)	(-1.98)	(-1.53)	(-0.83)	(-0.20)	(-0.04)	(-0.14)	(0.03)
	adj. $R^2$	12.22%	14.70%	14.20%	13.21%	11.55%	10.10%	8.33%	7.33%
$MOM12^{nb}$	Coefficient	0.0000	-0.006	-0.007	-0.010	-0.012	-0.012	-0.010	-0.008
	(t-stat)	(-0.01)	(-0.58)	(-0.80)	(-1.28)	(-1.42)	(-1.55)	(-1.35)	(-1.18)
	adj. $R^2$	11.94%	13.59%	13.46%	13.67%	12.91%	11.71%	9.45%	8.15%
$MOM12^{spr}$	Coefficient	-0.0003	-0.037	-0.030	-0.026	-0.016	-0.005	0.002	0.001

	(t-stat)	(-0.68)	(-0.92)	(-0.99)	(-1.15)	(-0.80)	(-0.26)	(0.11)	(0.06)
	adj. $R^2$	12.23%	13.85%	13.50%	13.08%	11.66%	10.12%	8.32%	7.33%
<i>MOM6<sup>nb</sup></i>	Coefficient	0.0000	0.003	0.002	0.000	-0.002	-0.003	-0.002	-0.001
	(t-stat)	(-0.16)	(0.29)	(0.28)	(-0.03)	(-0.32)	(-0.50)	(-0.41)	(-0.30)
	adj. $R^2$	11.95%	13.39%	13.14%	12.72%	11.59%	10.24%	8.39%	7.36%
<i>MOM6<sup>spr</sup></i>	Coefficient	-0.0004	-0.042	-0.026	-0.027	-0.023	-0.014	-0.008	-0.007
	(t-stat)	(-0.68)	(-0.93)	(-0.71)	(-1.08)	(-1.09)	(-0.66)	(-0.33)	(-0.27)
	adj. $R^2$	12.30%	13.97%	13.36%	13.07%	11.79%	10.22%	8.35%	7.37%
<i>SL<sup>nb</sup></i>	Coefficient	0.0000	-0.003	-0.005	-0.009	-0.011	-0.011	-0.011	-0.008
	(t-stat)	(0.45)	(-0.38)	(-0.59)	(-0.91)	(-0.94)	(-0.89)	(-0.98)	(-0.72)
	adj. $R^2$	12.03%	13.39%	13.25%	13.32%	12.51%	11.21%	9.59%	8.05%
<i>SL<sup>spr</sup></i>	Coefficient	-0.0007	-0.068	-0.066	-0.084	-0.083	-0.084	-0.085	-0.072
	(t-stat)	(-1.40)	(-2.04)	(-2.48)	(-2.91)	(-2.59)	(-2.65)	(-3.14)	(-2.94)
	adj. $R^2$	13.34%	15.23%	15.14%	16.62%	15.73%	14.80%	13.69%	11.73%
<i>CV<sup>nb</sup></i>	Coefficient	0.0002	0.012	0.004	0.0001	-0.001	0.0000	-0.0001	-0.0005
	(t-stat)	(1.12)	(0.94)	(0.34)	(0.01)	(-0.05)	(0.00)	(-0.01)	(-0.06)
	adj. $R^2$	13.02%	13.97%	13.16%	12.72%	11.52%	10.10%	8.31%	7.33%
<i>CV<sup>spr</sup></i>	Coefficient	0.0006	0.034	-0.008	-0.019	-0.016	-0.006	-0.008	-0.011
	(t-stat)	(0.97)	(0.62)	(-0.18)	(-0.44)	(-0.38)	(-0.14)	(-0.20)	(-0.31)
	adj. $R^2$	12.76%	13.65%	13.12%	12.85%	11.62%	10.12%	8.34%	7.40%

Table 7. Horse race with spreading factors

This table presents the predictive multivariate regressions with spreading factors of our interests. We include  $BM^{spr}$ ,  $CR_H^{spr}$ ,  $CR_L^{spr}$ ,  $SL^{spr}$ , and  $CV^{spr}$  for  $F_t$  in Eq (1). Model 1 includes no controlling variable ( $C_t$ ), and Models 2 and 3 include controlling variables. As in Section 4.2, Model 2 includes macroeconomic factors, TB, TERM, DEF, and CAY, and Model 3 includes equity risk factors, RMRF, SMB, and HML as controlling variables. The dependent variable is  $GDP\ growth_{t+1Q,t+hQ}$  which is the GDP growth for future  $h$  quarters from quarter  $t+1Q$  to quarter  $t+hQ$  for  $h = 1$  to 8. For each regression, we report the coefficient on the commodity futures risk factors, their t-statistics which are the number in parentheses, and the adjusted  $R^2$  value of the regression. The t-statistics are computed using the Newey and West (1987) method with  $2h+1$  lags. The sample period is from 1982:1Q to 2017:3Q.

Model	Variable		Horizon ( $h$ )							
			1	2	3	4	5	6	7	8
1	$BM^{spr}$	Coefficient	0.001	0.032	0.021	0.007	-0.007	-0.020	-0.022	-0.022
		(t-stat)	(1.07)	(0.51)	(0.40)	(0.16)	(-0.18)	(-0.56)	(-0.68)	(-0.69)
	$CR_H^{spr}$	Coefficient	0.000	-0.010	0.001	0.005	0.040	0.049	0.037	0.043
		(t-stat)	(0.21)	(-0.16)	(0.01)	(0.09)	(0.73)	(1.04)	(1.01)	(1.22)
	$CR_L^{spr}$	Coefficient	0.000	-0.033	-0.018	-0.010	0.002	0.009	0.013	0.009
		(t-stat)	(-0.68)	(-0.61)	(-0.36)	(-0.22)	(0.04)	(0.18)	(0.26)	(0.19)
	$SL^{spr}$	Coefficient	-0.001	-0.062	-0.058	-0.074	-0.062	-0.059	-0.064	-0.052
		(t-stat)	(-1.32)	(-1.42)	(-1.52)	(-2.13)	(-1.69)	(-1.67)	(-2.07)	(-1.98)
	$CV^{spr}$	Coefficient	0.000	0.010	-0.029	-0.033	-0.021	-0.006	-0.007	-0.012
		(t-stat)	(0.29)	(0.18)	(-0.60)	(-0.74)	(-0.47)	(-0.15)	(-0.20)	(-0.34)
adj. $R^2$		-1.59%	-2.14%	-2.17%	-0.41%	0.09%	0.86%	1.57%	1.21%	
2	$BM^{spr}$	Coefficient	0.001	0.009	-0.001	-0.016	-0.027	-0.038	-0.036	-0.033
		(t-stat)	(0.78)	(0.16)	(-0.03)	(-0.37)	(-0.69)	(-1.08)	(-1.18)	(-1.17)
	$CR_H^{spr}$	Coefficient	0.000	-0.033	-0.016	-0.007	0.033	0.046	0.038	0.045
		(t-stat)	(-0.26)	(-0.67)	(-0.32)	(-0.13)	(0.69)	(1.06)	(1.09)	(1.34)
	$CR_L^{spr}$	Coefficient	0.000	0.003	0.013	0.020	0.030	0.034	0.036	0.028
		(t-stat)	(0.07)	(0.06)	(0.28)	(0.46)	(0.69)	(0.78)	(0.89)	(0.75)
	$SL^{spr}$	Coefficient	0.000	-0.044	-0.044	-0.063	-0.055	-0.053	-0.060	-0.049
		(t-stat)	(-0.86)	(-0.90)	(-0.99)	(-1.61)	(-1.41)	(-1.42)	(-1.80)	(-1.67)

	$CV^{spr}$	Coefficient	0.000	0.002	-0.042	-0.052	-0.040	-0.024	-0.022	-0.026
		(t-stat)	(0.26)	(0.04)	(-0.96)	(-1.21)	(-0.97)	(-0.62)	(-0.70)	(-0.91)
		adj. $R^2$	18.75%	12.85%	9.26%	10.95%	10.90%	11.13%	12.68%	12.76%
3	$BM^{spr}$	Coefficient	0.001	0.061	0.050	0.036	0.021	0.007	0.003	-0.001
		(t-stat)	(1.49)	(0.91)	(0.85)	(0.68)	(0.44)	(0.16)	(0.07)	(-0.02)
	$CR_H^{spr}$	Coefficient	0.000	-0.016	-0.003	0.003	0.040	0.050	0.039	0.045
		(t-stat)	(0.18)	(-0.28)	(-0.05)	(0.05)	(0.65)	(0.89)	(0.82)	(1.02)
	$CR_L^{spr}$	Coefficient	-0.001	-0.045	-0.032	-0.024	-0.012	-0.005	-0.001	-0.002
		(t-stat)	(-0.95)	(-0.77)	(-0.58)	(-0.52)	(-0.27)	(-0.12)	(-0.02)	(-0.04)
	$SL^{spr}$	Coefficient	-0.001	-0.087	-0.080	-0.094	-0.081	-0.075	-0.078	-0.063
		(t-stat)	(-1.89)	(-2.18)	(-2.24)	(-2.77)	(-2.25)	(-2.15)	(-2.53)	(-2.30)
	$CV^{spr}$	Coefficient	0.000	0.012	-0.027	-0.032	-0.021	-0.007	-0.008	-0.010
		(t-stat)	(0.33)	(0.22)	(-0.61)	(-0.74)	(-0.49)	(-0.16)	(-0.20)	(-0.28)
		adj. $R^2$	13.55%	13.96%	13.22%	14.58%	13.55%	12.60%	11.30%	9.52%

Table 8. Predictability of the high- and low-slope spreading factors

This table exhibits predictability of the high- and low-slope spreading factors ( $SL_H^{spr}$  and  $SL_L^{spr}$ , respectively). We consider three models including the high-slope spreading factor, the low-slope spreading factor, and both the high- and low-slope spreading factors as  $F_t$  in Eq. (1), respectively. Models 1, 4, and 7 (Models 2, 5, and 8) are the ones with the high-slope (low-slope) spreading factor, and Models 3, 6, and 9 are the ones with both the high- and low-slope spreading factors. In addition, for controlling variables ( $C_t$ ) in Eq. (1), Models 1, 2, and 3 include no controlling variables, and Models 4, 5, and 6 (Models 7, 8, and 9) include macroeconomic factors, TB, TERM, DEF, and CAY (equity risk factors, RMRF, SMB, and HML). For each regression, we report the coefficient on the commodity futures risk factors, their t-statistics which are the number in parentheses, and the adjusted  $R^2$  value of the regression. The t-statistics are computed using the Newey and West (1987) method with  $2h+1$  lags. The sample period is from 1982:1Q to 2017:3Q.

Model	Variables	Horizon ( $h$ )								
		1	2	3	4	5	6	7	8	
1	$SL_H^{spr}$	Coefficient	-0.120	-0.047	-0.080	-0.074	-0.082	-0.067	-0.055	-0.054
		(t-stat)	(-1.97)	(-0.82)	(-1.72)	(-1.61)	(-1.93)	(-1.64)	(-1.58)	(-1.65)
		adj. $R^2$	1.64%	-0.25%	0.89%	0.86%	1.38%	0.85%	0.47%	0.50%
2	$SL_L^{spr}$	Coefficient	0.095	0.022	0.035	0.046	0.089	0.117	0.131	0.135
		(t-stat)	(1.42)	(0.31)	(0.58)	(0.80)	(1.38)	(1.70)	(1.94)	(2.29)
		adj. $R^2$	0.37%	-0.60%	-0.45%	-0.24%	1.10%	2.70%	3.92%	4.67%
3	$SL_H^{spr}$	Coefficient	-0.121	-0.047	-0.081	-0.075	-0.083	-0.069	-0.058	-0.057
		(t-stat)	(-1.96)	(-0.82)	(-1.71)	(-1.62)	(-1.94)	(-1.70)	(-1.72)	(-1.86)
	$SL_L^{spr}$	Coefficient	0.097	0.023	0.037	0.048	0.091	0.119	0.133	0.136
		(t-stat)	(1.46)	(0.32)	(0.60)	(0.82)	(1.41)	(1.72)	(1.97)	(2.35)
		adj. $R^2$	2.07%	-0.85%	0.47%	0.65%	2.56%	3.65%	4.54%	5.35%
4	$SL_H^{spr}$	Coefficient	-0.069	0.000	-0.052	-0.049	-0.059	-0.040	-0.036	-0.041
		(t-stat)	(-1.12)	(-0.57)	(-0.86)	(-0.79)	(-1.02)	(-0.73)	(-0.74)	(-0.93)
		adj. $R^2$	32.12%	20.44%	15.49%	11.48%	11.41%	9.84%	9.14%	10.11%
5	$SL_L^{spr}$	Coefficient	0.074	0.000	0.013	0.028	0.070	0.099	0.112	0.114
		(t-stat)	(1.17)	(0.10)	(0.20)	(0.49)	(1.11)	(1.46)	(1.68)	(2.04)
		adj. $R^2$	32.11%	20.21%	14.91%	11.02%	11.63%	12.12%	12.58%	13.98%
6	$SL_H^{spr}$	Coefficient	-0.070	0.000	-0.053	-0.050	-0.060	-0.042	-0.039	-0.044

		(t-stat)	(-1.11)	(-0.57)	(-0.86)	(-0.80)	(-1.05)	(-0.78)	(-0.82)	(-1.04)
	$SL_L^{spr}$	Coefficient	0.075	0.000	0.014	0.029	0.071	0.100	0.113	0.116
		(t-stat)	(1.18)	(0.11)	(0.22)	(0.51)	(1.13)	(1.46)	(1.69)	(2.06)
		adj. $R^2$	32.41%	19.83%	14.87%	10.97%	12.02%	12.02%	12.45%	14.11%
7	$SL_H^{spr}$	Coefficient	-0.131	-0.001	-0.101	-0.090	-0.093	-0.069	-0.062	-0.065
		(t-stat)	(-1.68)	(-1.53)	(-2.41)	(-2.35)	(-2.79)	(-2.34)	(-2.48)	(-2.72)
		adj. $R^2$	7.20%	13.41%	15.61%	15.20%	15.34%	13.13%	11.55%	10.08%
8	$SL_L^{spr}$	Coefficient	0.087	0.000	0.031	0.039	0.076	0.102	0.112	0.110
		(t-stat)	(1.30)	(0.56)	(0.60)	(0.82)	(1.31)	(1.59)	(1.74)	(1.97)
		adj. $R^2$	5.38%	12.13%	13.50%	13.42%	14.19%	14.48%	13.96%	12.46%
9	$SL_H^{spr}$	Coefficient	-0.132	-0.001	-0.101	-0.090	-0.094	-0.070	-0.064	-0.067
		(t-stat)	(-1.68)	(-1.53)	(-2.39)	(-2.33)	(-2.74)	(-2.32)	(-2.56)	(-2.89)
	$SL_L^{spr}$	Coefficient	0.089	0.000	0.032	0.040	0.078	0.103	0.113	0.111
		(t-stat)	(1.33)	(0.58)	(0.63)	(0.84)	(1.35)	(1.61)	(1.77)	(2.03)
		adj. $R^2$	7.61%	12.94%	15.15%	14.89%	16.22%	15.50%	14.84%	13.69%