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Can commodity futures risk factors predict economic growth?

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Abstract

This paper examines whether commodity futures risk factors can predict future economic growth. We test risk factors capturing various spot or term premia and find that, after controlling for traditional predictors, only three factors capturing term premia on the basis-momentum, basis, and change in slope remain significant predictors for future economic growth, especially for long horizons. Moreover, the change in slope factor appears to be the strongest and most robust predictor among them. Our findings highlight the importance of the term premia, rather than the spot premia on which the literature has mainly focused.

JEL classification: G10; G11; G12

Keywords: Commodity futures; basis; momentum; term premia; economic growth; ICAPM

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1. Introduction

Merton's (1973) intertemporal capital asset pricing model (ICAPM) suggests that, if there is stochastic variation in investment opportunities, risk premia are likely to be related to innovations in the state variables that describe the investment opportunities. Therefore, if a risk factor acts as a state variable in the context of Merton's (1973) ICAPM, it should be able to capture information about fundamental risk in the economy that would affect future investment opportunities. Following this notion, Liew and Vassalou (2000) examine whether three equity risk factors—value, size, and momentum factors—can predict future economic states measured by gross domestic product (GDP) growth and report that value and size factors exhibit significant predictability for future GDP growth. Maio and Santa-Clara (2012) examine various multifactor models in equity markets and whether these factors can be interpreted as state variables from the perspective of the ICAPM.

This paper examines whether the commodity futures risk factors recently suggested and unique to commodity futures—as noted by Szymanowska et al., 2014, hereafter SRGN; Bakshi et al., 2019, hereafter BGR; Boons and Prado, 2019, hereafter BP—can predict future economic growth in Merton's sense. There has been a long debate regarding which factors are priced as risk factors in the commodity futures markets, and the literature has not yet reached any consensus.[1] Recent studies on commodity futures have suggested new multifactor models that are unique to commodity futures markets. SRGN focus on the basis, the difference between the

[1] For example, Miffre and Rallis (2007) employ the returns on a government bond index, the Standard & Poor's 500 composite index, and the Goldman Sachs Commodity Index as risk factors. However, Daskalaki et al. (2014) empirically examine models that are popular in the finance literature, such as the macroeconomic factor model or the 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 commodity markets, which shows that commodity markets are segmented from other markets, especially from the equity market.

futures and spot prices, which has long been believed to be a predictor of expected futures returns based on traditional theories, such as the theory of storage or the hedging pressure hypothesis. They develop a three-factor model based on the basis that can explain various spot and term premia. BGR suggest another three-factor model and show that it successfully explains the cross-sectional variation of commodity returns. More recently, BP suggest a new return predictor, named basis-momentum, and show that factors based on basis-momentum are significantly priced in commodity futures markets, even after controlling for BGR's and SRGN's factors.

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

Our paper is motivated by that of Liew and Vassalou (2000), in the sense that we examine whether risk factors suggested in the literature predict future economic growth, but it differs from theirs and others, such as Harvey (1989) and Vassalou (2003), because our main focus lies in the risk factors suggested in commodity futures markets. The literature on commodity futures markets has reported that commodity futures factors are quite weakly related to other markets' factors.[2] 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.

[2] For example, with respect to the commodity futures momentum factors, Miffre and Rallis (2007) and Kang and Kwon (2017) report that commodity futures momentum cannot be fully explained by bond and equity market factors or other equity risk factors. Daskalaki et al. (2014) document that a macroeconomic factor model and an equity-factor model fail to explain commodity futures returns.

Since Merton's ICAPM (1973) implies that a state variable should capture economy-wide risks and thus corresponding stochastic discount factor can explain premia in various asset markets, it can be questionable whether commodity risk factors showing such low correlations (especially with traditional equity factors) are good candidates for state variables in the ICAPM. We expect that investigating commodity futures factors can be noteworthy in twofold. First, according to the literature on the intermediary asset pricing (Etula, 2013; Adrian et al., 2014; He et al., 2017), a risk factor capturing the intermediary's risk is priced in various asset markets including equity, bond, and commodity futures. These previous studies shed light on the possibility of existence of common risk factors across assets, and thus suggest that risk factors in commodity futures markets can be also significantly priced in other asset markets. Second, commodities are essential inputs in the production of goods and so their prices can vary with the economic state (Kilian, 2009; Tang and Xiong, 2012). Thus, we expect that commodity futures risk factors may have predictive power for future economic growth and low correlations with traditional factors may indicate the possibility of unique information for future economic growth that the existing factors do not capture.

In this paper, we test a large number of commodity risk factors that have been more recently developed.[3] More importantly, our test factors can be categorized into two types, one capturing the spot premium and the other capturing the term premium, and we can thus investigate which component has more significant economic content. Specifically, following SRGN, we consider two types of factors, one measured by a *nearby* return (the return on the nearest contract) capturing a spot premium, and the other measured by a *spreading* return

[3] Previously, few studies test the predictability of commodity futures risk factors (Fernandez-Perez et al., 2017; Kang and Kwon, 2017), and they cover only a small number of them. Kang and Kwon (2017) test whether the momentum and basis factors can predict future GDP growth, and Fernandez-Perez et al. (2017) investigate three factors, that is, the basis, hedging pressure, and momentum factors.

(difference between the returns on the nearest and second-nearest contracts, also known as the first- and second-nearby returns) capturing a term premium. We take into account all factors suggested by SRGN, BGR, and BP. Specifically, the SRGN model includes three factors: the nearby return of the High4-minus-Low4 basis portfolio (CR^{nb}), the spreading return of the High4 basis portfolio (CR_H^{spr}) and the Low4 basis portfolio (CR_L^{spr}), respectively. The BGR model includes three factors: the average nearby return of all sample commodity futures (AVG^{nb}), the nearby return of the High4-minus-Low4 basis portfolio, as for SRGN (CR^{nb}), and 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 six months, respectively). The BP model includes two factors: the nearby and spreading returns of the High4-minus-Low4 basis-momentum portfolio, BM^{nb} and BM^{spr}, respectively. Lastly, we further decompose BM^{nb} (BM^{spr}) into two factors: the nearby (spreading) return of the High4-minus-Low4 change in slope portfolio, SL^{nb} (SL^{spr}) and the High4-minus-Low4 curvature portfolio, CV^{nb} (CV^{spr}), respectively.

Our results show that AVG^{nb} and BM^{nb} have significant predictive power for future economic growth within a one-year horizon. In a longer horizon, from one to two years, $MOM12^{nb}$, BM^{spr}, and CR_H^{spr} also show significant predictive power for future economic growth. Moreover, if we compare the predictive power of SL^{spr} with that of CV^{spr}, SL^{spr} appears to be the main driver of BM^{spr}'s predictability for future economic growth.

Next, we investigate the predictability of commodity futures risk factors for future economic growth after controlling for traditional economic growth predictors, macroeconomic factors, and equity risk factors, to examine whether commodity futures risk factors contain information independent of these traditional predictors. Controlling for traditional predictors affects the predictability of commodity futures risk factors differently. For example, we find that the predictive power of $MOM12^{nb}$ can be improved by including macroeconomic factors,

which could indicate that $MOM12^{nb}$ jointly plays a role as a state variable with the macroeconomic factors, but becomes insignificant if equity factors are controlled for. However, we find that two long-term predictors, BM^{spr} and CR_H^{spr}, consistently remain significant, even after controlling for other predictors. Moreover, between the two components of BM^{spr}, we find that SL^{spr} consistently has strong and robust predictability for future GDP growth, especially in the long term. Our results exhibit that the predictive power of commodity futures nearby factors for future GDP growth is largely subsumed by other factors, either macroeconomic factors or equity risk factors. Moreover, our results highlight the importance of spreading factors in commodity futures markets as a state variable in the context of Merton's ICAPM, because they seem to embody an economic source unique to commodity futures markets and significantly predict future economic growth. The most striking finding is that the change in slope spreading factor, which captures the term premium on the variation in the slope of the commodity futures term structure, consistently shows strong and robust predictability for future GDP growth, especially in the long term.

In terms of the sign of predictability, our results show that AVG^{nb}, BM^{nb}, and CR_H^{spr} positively forecast future economic growth, while $MOM12^{nb}$, BM^{spr}, and SL^{spr} do so negatively. The sign of the coefficients on commodity risk factors is also important, as well as their significance, because they suggest how these factors are related to future investment opportunities. The question of how commodity futures risk factors forecast future investment opportunities has rarely been investigated in the literature, and it is thus challenging to suggest interpretations of our results, that is, why some factors positively forecast future economic growth and others do so negatively. Thus, we further test whether the factors exhibit consistency in forecasting future investment opportunities, following Maio and Santa-Clara (2012) and Fernandez-Perez et al. (2017). Our empirical findings provide rather weak but consistent evidence for the short-term predictors BM^{nb} and AVG^{nb}. The long-term predictors

$MOM12^{nb}$, BM^{spr}, CR_H^{spr}, and SL^{spr} also show consistent and even stronger results in predicting future market returns and variance. Though the economic content of commodity futures risk factors is our main interest in this paper, we expect that relations with future investment opportunities contribute to the understanding of commodity factors' predictive power for future economic growth.

Lastly, since our empirical results shed light on the importance of the spreading factors in relation with future economic states, 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 the 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 demonstrate 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, SL_H^{spr} and SL_L^{spr}. We investigate whether one of these two lags of SL^{spr} mainly leads predictability or whether they symmetrically play a critical role in predicting future GDP growth. We find considerable differences between SL_H^{spr} and SL_L^{spr}. Specifically, our results show that the robust long-term predictive power of the spreading factor mainly stems from SL_L^{spr}, while the predictive power of SL_H^{spr} appears to be highly sensitive to the control 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 short legs of SL^{spr} could have different information.

The remainder of the paper is organized as follows. Section 2 describes our data. Section 3 describes the commodity futures risk factors that we consider. Section 4 examines the predictive power of commodity futures risk factors for future economic growth. Section 5 examines whether factors have predictive power for investment opportunities and whether the results are consistent with economic growth predictability. In Section 6, we further investigates spreading factors. Lastly, Section 7 concludes the paper.

2. Data

We use GDP growth as a measure of economic growth, following the majority of the literature (Lew and Vassalou, 2000; Vassalou, 2003; Kang and Kwon, 2017). The quarterly (seasonally adjusted) series of GDP growth is obtained from the Organisation for Economic Co-operation and Development.

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 for month $t + 1$, at the end of month t, we take a position in the

futures contract whose maturity date is after the end of month $t + 1$.[4] Similarly, we also construct the time series of the second-nearby returns for each of the commodity futures. Next, using the series of first- and second-nearby returns, we construct two types of returns, one capturing the spot premium and the other 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 Section 3 for further details). The daily data obtained from Datastream span the period from January 1979 to December 2017, and the quarterly factor series span the period from the first quarter of 1980 (1980:1Q) to the fourth quarter of 2017 (2017:4Q).

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*), the term spread (*TERM*), the default spread (*DEF*), and the variable *CAY* suggested by Lettau and Ludvigson (2000). Specifically, we use the three-month Treasury bill rate for *TB*, the yield spread between 10-year and one-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 obtained from Lettau's website.[5] For equity risk factors, we employ Fama and French's (1993) three-factor model,

[4] Our choice is consistent with that of the majority of commodity studies (Gorton et al., 2012; Hong and Yogo, 2012; BGR).

[5] See https://sites.google.com/view/martinlettau/data.

which includes the market factor (*RMRF*), the size factor (*SMB*), and the value factor (*HML*).[6] The quarterly return series of these factors are obtained from French's website.[7] In Sections 4.2 and 5, due to the availability of data for the control variables, the sample period is limited to 1982:1Q to 2017:3Q. Lastly, following Liew and Vassalou (2000), all returns and growth rates used are continuously compounded.

3. Commodity Futures Risk Factors

We employ risk factors recently documented by BGR, SRGN, and BP, since they are unique to commodity futures markets. To construct these factors, we first define basis (B_t) and momentum ($M(t-11,t)$) following BP:

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

where $F_t^{T_i}$ indicates the *i*th-nearby futures price for month *t* and $R_{fut,t}^{T_i}$ indicates *i*th-nearby futures return for month *t*.[8] While BGR originally suggest the six-month momentum factor, BP examine the 12-month momentum factor. Since the 12-month ranking period is commonly

[6] 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.

[7] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[8] In predictive regressions, we use the logarithmic returns on portfolios as factors, following Liew and Vassalou (2000), but, in defining the variables to form the portfolios, we follow the original methods, using normal returns, and not their logarithms.

used in the momentum literature, we focus on the 12-month momentum ($M(t-11,t)$), but we also consider the six-month momentum ($M(t-5,t)$), following the original method of BGR.

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

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

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, respectively, 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* = {High4, Mid, Low4}, following BP, where High4 (Low4) includes the four commodities with the highest-ranked (lowest-ranked) signal and Mid includes the remaining commodities. We construct portfolios based on the basis, the 12-month momentum, the six-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 captured by taking a long position in the first-nearby contract, which we call the *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, which we call the *spreading return*. For each

portfolio, we compute the equal-weighted average of the 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 for 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 six 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}). The factor 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}), and (2) the nearby (spreading) return of the High4-minus-Low4 curvature portfolio, CV^{nb} (CV^{spr}).

[Insert Table I about here]

Table I presents the summary statistics of our test factors. Though BGR consider only nearby return factors, we additionally report the summary statistics of the spreading factors, which are the average spreading returns of all the 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 six months, respectively).

Panel A of Table I shows the average, standard deviation, skewness, kurtosis, minimum, and maximum of the quarterly factor values during the sample period. Consistent with the

results of SRGN and BP, Panel A shows that nearby factors tend to be much larger than the spreading factors. For example, the basis-momentum nearby factor (BM^{nb}) has a mean of 1.651%, while the basis-momentum spreading factor (BM^{spr}) has a mean of 0.722%. In addition to the mean, the nearby factors show much larger standard deviations than the spreading 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, on a quarterly basis, the spreading and nearby factors have the same signs in terms of the mean, except for 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. For example, CR_L^{spr} shows a much larger average and standard deviation than CR_H^{spr}. SRGN document that the (High4-minus-Low4) basis spreading factor (CR^{spr}) fails to explain various term premia, but if it is separated into the 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.

~~The two rightmost columns of Panel A report the AR(1) coefficients and their t-statistics, respectively. Stambaugh (1999) document that the slope coefficients can be biased if a predictor is strongly persistent and endogenous. It is very little known about the persistence properties of commodity factors, especially spreading factors, and so we investigate whether our test factors are strongly persistent, which can be critical in predictive tests. Our results show that all test factors show extremely low and statistically insignificant AR(1) coefficients except BM^{spr}. In case of BM^{spr}, even though the coefficient is statistically significant (t-stat. = 2.03), the size of the coefficient is small as 0.165. Stambaugh (1999) note that the bias shrinks as the serial autocorrelation (ρ) approaches zero, and thus we expect that the bias caused by the serial~~

~~correlation should be small. Moreover, in untabulated results, we also check the AR(2) coefficient of BM^{spr} and find that the coefficient becomes much smaller and insignificant (coefficient = 0.051 with t-stat. = 0.61).~~

Panel B of Table I presents the correlations among the commodity futures risk factors. The nearby and spreading factors of each predictor show correlations larger than 40%. The correlation between the curvature factors is a bit low, 0.391, but the correlation between the average factors is very low, 0.046. With respect to the basis factors, the basis spreading factor shows a stronger correlation, in terms of the absolute magnitude, with the short leg, which is CR_L^{spr}. Specifically, the correlation between CR^{spr} and CR_L^{spr} is -0.828, while that between CR^{spr} and CR_H^{spr} is 0.549.

In general, Panel B of Table I suggests that commodity futures risk factors are substantially correlated with each other. For example, the basis-momentum and basis nearby factors have a correlation of -0.433, and the basis-momentum and momentum nearby factors have a correlation of 0.335. These results are in stark contrast to the correlations between commodity futures risk factors and equity risk factors (reported in Table AI), since 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 have not yet been explored and which are expected to be distinct from existing factors, such as equity factors or macroeconomic factors, which have been mainly examined in previous studies (Harvey, 1989; Liew and Vassalou, 2000; Vassalou, 2003).

4. Can Commodity Risk Factors Predict GDP Growth?

In this section, we examine whether commodity risk factors can predict future GDP growth. We 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 h future quarters from quarter t + $1Q$ to quarter $t + hQ$ for h = 1, …, 8, F_t indicates the set of commodity futures risk factors for quarter t, and C_t is the set of control variables for quarter t.[9] 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 factors 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 of future GDP growth on each of commodity futures risk factors. Next, we examine multivariate regression models that include a subset of commodity futures risk factors in our consideration as independent variables. In Table II, we report the coefficients on commodity futures risk factors, their statistical significance (t-statistics), and the adjusted R^2 values of the regression to determine the explanatory power.

[9] Since Equation (1) requires overlapping observations (h-1 quarters for h = 1, …, 8), following Cochrane and Piazzesi (2005), we compute the t-statistics using the Newey–West (1987) method with more than two times as many lags as the overlap, which is 2h.

[Insert Table II about here]

Table II shows that many of the commodity futures risk factors fail to predict future economic growth. First, all the nearby factors, except the basis-momentum, average, and 12-month momentum factors, show insignificant coefficients and even negative adjusted R^2 values for all horizons. Moreover, the predictability of BM^{nb} is limited only to the next quarter. The coefficient on BM^{nb} is marginally significant (t-stat. = 1.71) only for h = 1, and it becomes insignificant for longer terms. By contrast, AVG^{nb} shows stronger predictability up to five quarters. The results also show that its predictability for future GDP growth decreases as h increases. In the case of h = 1, the adjusted R^2 value is 9.07%, which is the largest among all the test factors, and the adjusted R^2 value monotonically decreases as h increases.

While two nearby factors, BM^{nb} and AVG^{nb}, show positive and significant results in the short term, the 12-month momentum nearby factor shows a different pattern: $MOM12^{nb}$ exhibits a negatively significant relation with future GDP growth from h = 6 onward. The negative relation between $MOM12^{nb}$ and future GDP growth is consistent with the findings of Kang and Kwon (2017), but the interesting feature in Panel B of Table I is that $MOM12^{nb}$ is positively correlated with BM^{nb} and AVG^{nb}, which positively predict 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.[10] We expect $MOM12^{nb}$, BM^{nb}, and AVG^{nb} could capture different risks, even though they are positively correlated with each other, and thus show considerable differences in predicting economic growth. We discuss more about the sign of the coefficients

[10] More specifically, BGR argue that CR^{nb} is related to global equity volatility and $MOM6^{nb}$ is related to speculative activity in the commodity futures market.

on risk factors—whether they predict future economic growth positively or negatively—in Section 5.

Interestingly, the spreading factors show better predictability than the nearby factors in the long term. For example, BM^{spr} negatively predicts the next four to eight quarters of GDP growth, and CR_H^{spr} positively predicts the next five to eight quarters of GDP growth. Both factors show that the size of the coefficients and the adjusted R^2 values monotonically increase as the horizon (h) extends, in general. SRGN argue that the long and short legs of CR^{spr}, CR_H^{spr} and CR_L^{spr} play distinctive roles, especially in explaining the term premia. Consistent with SRGN, our results imply the asymmetric performance of these two factors in predicting future economic growth. Only CR_H^{spr} shows significant predictability for future GDP growth. More specifically, CR_H^{spr} significantly predicts two-year (eight-quarter) growth, with an adjusted R^2 of about 3%.

The factor BM^{spr} can be decomposed into the change in slope factor (SL^{spr}) and the average curvature factor (CV^{spr}). Between these two components, we find that the predictability of BM^{spr} mainly stems from the change in slope spreading factor. Specifically, SL^{spr} negatively predicts 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 future GDP growth than BM^{spr} does. In the case of SL^{spr}, the adjusted R^2 values range from -0.24% to 4.64%, and they are all over 3% especially for long horizons. In the case of BM^{spr}, the adjusted R^2 values are at most 2.16%. These results are 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 highlight the importance of the

change in slope (spreading) factor containing information about future economic states, rather than the curvature (spreading) factor.

Lastly, most of the adjusted R^2 values reported in Table II seem quite small, even for the significant cases. However, Harvey (1989) reports that the equity market factors can explain only about 5% of the variation of future GDP growth. As we report in Panel A of Tables IV and V, the macroeconomic and equity factors also generate 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, our findings in Table II do not seem ignorable.

Next, we run multivariate regressions with various subsets of commodity futures risk factors. Specifically, in Equation (1), we let F_t be a subset of commodity futures risk factors and we do not include any control variables (C_t). We basically consider the BP, SRGN, and BGR models. Model 1 is the BP model including BM^{nb} and BM^{spr}, and Model 2 is an extended BP model that includes AVG^{nb} in addition to the BP factors. Model 3 is the SRGN model including CR^{nb}, CR_H^{spr}, and CR_L^{spr}. Models 4 and 5 are the BGR models—including AVG^{nb}, CR^{nb}, and MOM^{nb}—with $MOM12^{nb}$ and $MOM6^{nb}$, respectively. Models 6 and 7 are the decomposed BP models—including SL^{nb}, SL^{spr}, CV^{nb}, and CV^{spr}—without and with AVG^{nb}, respectively. By running multivariate regressions, we expect to see whether the predictability of a factor is subsumed by that of others and whether 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 III.

[Insert Table III about here]

The overall results in Table III are qualitatively similar to the univariate results in general, although the size and significance of the coefficients show some differences. First, according

to Models 1 and 2, the short-term predictability of BM^{nb} and the long-term predictability of BM^{spr} do not critically affect each other. The factor 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 coefficients on BM^{nb} become weaker as AVG^{nb} is included but still remain significant. In Model 3, consistent with Table II, only CR_H^{spr} shows significant predictability for future GDP growth. Models 4 and 5 show that momentum nearby factors based on the past 12 and six months have substantial differences in predicting future GDP growth, which is also consistent with the univariate cases. Lastly, in Model 6, the predictability of SL^{spr} is robust to other components of BM^{spr}, which are SL^{nb}, CV^{nb}, and CV^{spr}.

On the other hand, Table III also exhibits interesting differences compared to the univariate cases. The coefficients on AVG^{nb} show especially dramatic changes. For example, we find that the coefficients on AVG^{nb} are significant up to five quarters (h = 5) in Table II, but in Table III, after controlling for the basis-momentum nearby and spreading factors, we find that they are significant up to seven quarters (h = 7). Compared to Model 1, Model 2 shows improved adjusted R^2 values for all horizons, and BM^{spr} in Model 2 also exhibits slightly more significant results than in Model 1 in Table III and the univariate results in Table II. These findings suggest that AVG^{nb} and BM^{spr} can jointly work better as state variables in the context of Merton's (1973) ICAPM. The improved predictability in the multivariate models is also observed in Models 4 and 7. Specifically, Model 4 shows that the predictive power 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. The factor AVG^{nb} also generally shows improved results over all horizons except in the short term, especially in the case of h = 1. Table II reports that the coefficient on AVG^{nb} for h = 1 is 0.091, with a t-statistic equal to

2.11, while Model 7 in Table III shows a coefficient of 0.074, with a t-statistic of 1.77. These results imply that a subset of commodity futures factors could provide improved predictability if jointly considered.

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

4.2. Do Other Predictors Subsume the Predictability of Commodity Risk Factors?

In this section, we further consider other traditional predictors for future economic growth and examine the predictive power of commodity risk factors after controlling for these traditional predictors. Specifically, we employ two sets of controlling predictors: a set of macroeconomic factors (*TB, TERM, DEF*, and *CAY*) and another set of traditional risk factors in the equity market (*RMRF, SMB*, and *HML*).

We report the correlations among commodity futures risk factors and control variables in Table AI in the Appendix. Table AI confirms our motivation to focus on commodity futures risk factors that have not yet been explored and which are expected to be distinguished from existing factors, such as equity factors or macroeconomic factors, which previous studies mainly examine (Harvey, 1989; Liew and Vassalou, 2000; Vassalou, 2003). As noted in

previous sections, compared to the correlations among commodity futures risk factors themselves (Panel B of Table I), the 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.

We investigate the predictability of commodity futures risk factors after controlling for each of the two sets of controlling predictors. Specifically, in Equation (1), F_t is each individual commodity futures risk factor[11] and C_t is a set of control 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 IV), and then after controlling for equity risk factors (Table V).

[Insert Table IV about here]

First, Panel A of Table IV presents the results of the univariate and multivariate predictive regressions with only macroeconomic factors. The macroeconomic factors exhibit rather weak results in the univariate models, except for *DEF*, since this factor shows significant results for up to four quarters and the adjusted R^2 appears to be large, especially in the short term (e.g., 17.94% in the case of h = 1). The multivariate model suggests that the macroeconomic factors could work better jointly as state variables. In the multivariate model, in addition to *DEF*, *TERM* also shows a significant relation with future economic growth, even

[11] 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 we therefore report only the results using individual commodity futures risk factor in this section.

in the longer term, up to eight quarters, and the adjusted R^2 also shows much improved results compared to the univariate model of *DEF*. The improvement in the adjusted R^2 values seems notable, especially in the long term, since they increase from 6.09% to 10.41% in the case of h = 8.

Panel B of Table IV shows the multivariate results with each of the commodity futures risk factors and a set of the macroeconomic factors. The common feature in Panel B is that the coefficients on the commodity futures risk factors for the next quarter (h = 1) are largely reduced and become much less significant compared to those in Table II. Interestingly, the commodity futures factors that previously show significant predictability in the short term, AVG^{nb} and BM^{nb}, become insignificant, indicating that these factors' predictive power is subsumed by macroeconomic factors. For example, AVG^{nb} exhibits the largest and most significant coefficient for h = 1 in Table II (coeff. = 0.091, t-stat. = 2.11), but after macroeconomic factors are controlled for, it becomes 0.0003, with a t-statistic equal to 0.87.

By contrast, the commodity futures factors that previously exhibited significant results in the long term are found to be robust to macroeconomic factors. Specifically, we previously find that $MOM12^{nb}$, BM^{spr}, CR_H^{spr}, and SL^{spr} have significant predictability in the long term. In Table IV, they show slightly weaker results compared to the results in Table II, but many of their coefficients remain significant, especially from h = 5 to 8. For example, the coefficients on BM^{spr} from h = 5 to 8 range from -0.063 to -0.097, with t-statistics ranging from -2.58 to -1.74. The factor SL^{spr} shows a significant relation with future GDP growth from h = 6 to 8 and also substantially improves the adjusted R^2 values relative to the model with only macroeconomic factors. For example, in the case of h = 8, Panel A of Table IV reports that the multivariate macroeconomic model generates an adjusted R^2 value of 10.41%, but Panel B shows that, if SL^{spr} is additionally included, the adjusted R^2 value is increased to 13.26%.

The overall results in Table IV provide interesting implications. The commodity futures risk factors that previously show significant predictability for future GDP growth in the short term, AVG^{nb} and BM^{nb}, become insignificant in all test horizons after we control for the macroeconomic factors. These results suggest that the economic sources of these factors are related to the macroeconomic factors, and their predictive power is thus subsumed by these macroeconomic factors. By contrast, the long-term predictors $MOM12^{nb}$, BM^{spr}, CR_H^{spr}, and SL^{spr} remain significant, even after controlling for the macroeconomic factors. These results may imply that the economic sources of these factors differ from those of the macroeconomic factors.

[Insert Table V about here]

Next, we control for the traditional equity risk factors. In Panel A of Table V, we first examine the predictability of equity risk factors for comparison. The equity market factor, *RMRF*, exhibits the strongest predictability among the three factors in both the univariate and multivariate regressions. The coefficients on *RMRF* are positively significant in all test horizons, and the adjusted R^2 values decrease 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, …, 8). Compared to the multivariate model of macroeconomic factors in Panel A of Table IV, that of equity risk factors shows relatively low adjusted R^2 values that range from 8.06% to 13.99%. This result is also consistent with Harvey's (1989) finding that macroeconomic factors show much better performance in predicting future GDP growth than equity factors do.

Similar to Panel B of Table VI, in Panel B of Table V, we test the multivariate models whose 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 IV and V is that the coefficient on the commodity futures risk factor for the next quarter (h = 1) is largely reduced and becomes much less significant compared to the univariate results in Table II. Another common feature is that the predictability of AVG^{nb} becomes insignificant in both models. Panel B of Table V shows that the coefficients on AVG^{nb} are insignificant in all cases (t-statistics from -0.38 to 1.05). By contrast, another short-term predictor, BM^{nb} remains significant for at least the next quarter (h = 1). Table AI indeed suggests some differences between AVG^{nb} and BM^{nb}. The factors AVG^{nb} and BM^{nb} show comparable correlations with some of the macroeconomic factors, especially *DEF*, but BM^{nb} shows much weaker correlations with all three equity factors than AVG^{nb} does, ranging from -0.051 to 0.019. For example, the correlation between AVG^{nb} and *RMRF* is 0.215. In addition to our findings in Panel B of Table IV, Panel B of Table V additionally exhibits the different natures of AVG^{nb} and BM^{nb}, where AVG^{nb} seems to be more correlated with equity market risk, while BM^{nb} could be more related to the macroeconomic factors.

The equity and macroeconomic models also reveal other substantial differences. First, the predictive power of $MOM12^{nb}$, after equity factors are controlled for, is in stark contrast to that after macroeconomic factors are controlled for. Previously, Table III exhibits that $BM^{spr}, MOM12^{nb}$, and SL^{spr} could jointly work with AVG^{nb} as state variables, and Table IV also shows 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 V shows that $MOM12^{nb}$ becomes insignificant while the other two factors, BM^{spr} and SL^{spr}, remain significant. These results could imply that the predictability of $MOM12^{nb}$ is subsumed by the information content unique to the equity risk factors and distinct from the macroeconomic factors.

Second, the coefficients on BM^{spr} become much smaller and weaker after controlling for equity factors than those after controlling for macroeconomic factors though they still remain significant in the long term. By contrast, compared to the results in Table 2, SL^{spr} shows more significant results in Table 5 while it shows less significant results in Table 4. It shows highly significant results in all cases except h = 1, and it also notably improves the adjusted R^2 values in long-term horizons. For example, Panel A of Table V shows that the adjusted R^2 value for h = 8 is 8.06%, while it increases to 11.73% in Panel B of Table V if SL^{spr} is additionally included. The improvement of the adjusted R^2 values in the long term appears to be greatest with SL^{spr} , among all the commodity futures risk factors.

Lastly, CR^{spr} significantly predicts future GDP growth from h=5 to 8 after controlling for equity factors while it consistently shows the insignificant predictive power in the previous analyses. SRGN document that the long and short legs of CR^{spr} should be separately considered to explain the term premia of commodity futures. However, Table V exhibits increased coefficients on CR_H^{spr} and decreased coefficients on CR_L^{spr} after equity factors are controlled for. A possible explanation is that equity risk factors asymmetrically affect the long and short legs of CR^{spr}. In other words, by controlling for equity risk factors, CR^{spr} more effectively captures the differences between the long and short legs by reducing the asymmetric effect between them, and so CR^{spr} could act as a state variable jointly with equity risk factors. However, this is beyond the focus of this paper and we therefore leave it for future research.

To sum up, the predictive power of commodity futures risk factors shows substantial differences when we control for existing traditional predictors. Without controlling for these traditional predictors, we find that AVG^{nb} and BM^{nb} significantly predict future GDP growth in the short term, and $MOM12^{nb}$, BM^{spr}, CR_H^{spr}, and SL^{spr} do so in the long term. In this section, however, we find that only the long-term predictors remain significant after controlling

for macroeconomic factors. After controlling for equity risk factors, we find BM^{nb}, BM^{spr}, and CR_H^{spr} remain significant but become much weaker. The most important finding is that SL^{spr} consistently shows strong and robust predictability for future GDP growth, especially in the long term.

The commodity risk factors that show significant results in both analyses, after macroeconomic and equity risk factors are controlled for, are all spreading factors: BM^{spr}, CR_H^{spr}, and SL^{spr}. The literature on commodity futures has been mainly focused on nearby returns capturing the spot premia, before the pioneering work of SRGN led to distinguishing 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 but more challenging to explain with the factor model than the spot premia captured by the nearby return. Our results show that the predictive power of commodity futures nearby factors for future GDP growth is subsumed by existing factors, either macroeconomic or equity factors. Consequently, our results also highlight the importance of spreading factors, especially related to the shape of commodity futures term structure, as a state variable in the context of Merton's (1973) ICAPM. These factors seem to embody an economic source unique to commodity futures markets, as well as significantly predict future economic growth.

5. Predicting Future Investment Opportunities

Up to this point, we mainly focus on the significance of the coefficients on commodity futures risk factors indicating whether they significantly predict future economic growth, and pay less attention to their signs. However, the signs of the coefficients on commodity risk factors are also important, since they suggest how the factors are related to future investment opportunities. In this section, we conduct more direct analysis on the relation between the

commodity futures factors and investment opportunities and compare the results with our findings in Section 4.

Maio and Santa-Clara (2012) examine eight popular multifactor models in equity markets in terms of whether they forecast changes in investment opportunities. More specifically, they examine whether a risk factor can forecast long-term stock market returns and variance, which can represent the distribution of future investment opportunities.[12] Motivated by Maio and Santa-Clara, Fernandez-Perez et al. (2017) investigate whether three commodity futures risk factors—the term structure factor (which is equal to our basis nearby factor) and hedging pressure and momentum factors—can predict future long-term equity market returns and variance, along with future GDP growth. They report that these three factors show consistency in forecasting future market returns, market variance, and GDP growth. For example, the term structure factor negatively predicts future GDP growth, indicating that it forecasts downturns as a future economic condition. Consistent with this finding, this factor also appears to negatively predict future market returns and positively predict future market variance.

In Section 4, we find that some of our test factors have significant predictive power for future economic growth. Specifically, we find significant results for $\boldsymbol{AVG^{nb}}$ and $\boldsymbol{BM^{nb}}$ in the short term and $\boldsymbol{MOM12^{nb}}$, $\boldsymbol{BM^{spr}}$, $\boldsymbol{CR_H^{spr}}$, and $\boldsymbol{SL^{spr}}$ in the long term. With regard to their signs, our results show that $\boldsymbol{AVG^{nb}}$, $\boldsymbol{BM^{nb}}$, and $\boldsymbol{CR_H^{spr}}$ positively forecast future economic growth, while $\boldsymbol{MOM12^{nb}}$, $\boldsymbol{BM^{spr}}$, and $\boldsymbol{SL^{spr}}$ do so negatively. The literature has rarely investigated how commodity futures risk factors forecast future investment opportunities, and it is challenging to suggest interpretations of our results, why some of them positively forecast

[12] The ultimate goal of Maio and Santa-Clara (2012) differs from ours: they aim to investigate whether a multifactor model can be interpreted as a variant of the ICAPM, and therefore additionally examine whether the coefficient of the risk price has a sign consistent with (opposite to) the coefficients on the risk factor in the time-series regression for long-term market returns (variance).

future economic growth, while others do so negatively. To fill this gap, in this section, we further investigate whether the factors exhibit consistency in forecasting future investment opportunities.

We follow Maio and Santa-Clara (2012) and Fernandez-Perez et al. (2017) regarding equity market returns and variance as representative of future investment opportunities, and test predictability with the time-series regression. Specifically, we test the following models:

$$r_{M,(t+1Q,t+hQ)} = \alpha + \beta' F_t + \delta' C_t + \varepsilon_t \tag{2}$$

$$\sigma^2_{M,(t+1Q,t+hQ)} = \alpha + \beta' F_t + \delta' C_t + \varepsilon_t \tag{3}$$

where $r_{M,(t+1Q,t+hQ)}$ ($\sigma^2_{M,(t+1Q,t+hQ)}$) indicates market returns (variance) for the future h quarters, from quarter t + 1Q to quarter t + hQ for h = 1, …, 8; F_t indicates the set of commodity futures risk factors for quarter t, and C_t is the set of control variables for quarter t. Specifically, using the market portfolio excess returns provided by Kenneth French,[13] we compute $r_{M,(t+1Q,t+hQ)}$ as continuously compounded returns from quarter t + 1Q to quarter t + hQ, and $\sigma^2_{M,(t+1Q,t+hQ)}$ as the sum of squared daily market excess returns from quarter t + 1Q to quarter t + hQ. For F_t, we include each of the commodity futures risk factors, and in this section we focus only on AVG^{nb}, BM^{nb}, $MOM12^{nb}$, BM^{spr}, CR_H^{spr}, and SL^{spr}, excluding factors that show insignificant results in Table II.

[Insert Table VI about here]

[Insert Table VII about here]

We report the estimated results of Equations (2) and (3) in Tables VI and VII, respectively. In both tables, Panel A reports the results without any control variables and Panels

[13] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

B and C report the results after controlling for macroeconomic factors and equity factors, respectively.

First, Table VI shows similar results, regardless of the control variables. The factor BM^{nb} negatively and significantly predicts future market returns, except for the next quarter (h = 1), and AVG^{nb} also appears to negatively predict future market returns, especially in a long term. These results seem to contradict our previous findings that these factors positively predict future GDP growth. However, considering that they show significantly positive coefficients, especially in the short term, in Table II, the positive coefficient on AVG^{nb} and negative but insignificant coefficient on BM^{nb} for h = 1 seem to be consistent with the previous results. The other factors, $MOM12^{nb}$, BM^{spr}, CR_H^{spr}, and SL^{spr}, also show consistent results. Specifically, $MOM12^{nb}$, BM^{spr}, and SL^{spr} (CR_H^{spr}) negatively (positively) predict future market returns, as they negatively (positively) predict future economic growth. The change in slope spreading factor (SL^{spr}), which showed notably significant and robust results in the previous section, exhibits rather weak predictability for future market returns, as it shows significant coefficients only in a few cases, but at least it consistently shows negative coefficients in all cases.

The variance forecast also shows qualitatively similar results in all the panels of Table VII. The factor BM^{nb} shows a generally positive relation with future market variance, though the significance of the coefficients exhibit differences across models. However, more importantly, the factor exceptionally shows a much less significant or even negative coefficient for h = 1, which is consistent with Table VI, in the sense that it shows notable exceptions for h = 1 in Table VI as well. For example, Panel A of Table VII reports that the coefficient on BM^{nb} for h = 1 is -0.006, while it ranges from 0.013 to 0.045 for larger h (longer term). The factor AVG^{nb} also shows that its coefficients are large and negative in the case of h = 1. Though the

coefficients of AVG^{nb} appear to be statistically insignificant (t-statistic from -1.58 to -1.50), AVG^{nb} shows notably large adjusted R^2 values for h = 1. The results in Tables VI and VII do not provide strong support for the predictability of BM^{nb} or AVG^{nb} , since they show insignificant or opposite results, but the exceptional patterns for the case of h = 1 seem to be consistent with our expectations.

As we confirm in Table VI, $MOM12^{nb}$, BM^{spr}, CR_H^{spr}, and SL^{spr} also show results that are consistent with our expectations in Table VII. The factors that exhibit negative relations with future economic growth, that is, $MOM12^{nb}$, BM^{spr}, and SL^{spr}, show positive relations with future market variance. The factor CR_H^{spr}, which shows positive relations with future economic growth, shows negative results in Table VII. Interestingly, unlike the weak results in Table VI, SL^{spr} shows positively significant predictive power for future variance, especially in the long term. The adjusted R^2 values also appear to be the largest among the test factors in the long term. For example, Panel A of Table VII shows that the adjusted R^2 value of SL^{spr} for h = 1 is 3.23%, while others range from -0.76% to 1.88%. These results could imply that SL^{spr} is especially good at forecasting the second moment of future investment opportunities, market variance, compared to the first moment.

The overall results in Section 5 provide a more direct explanation why some factors positively predict future economic growth while others do so negatively. Though the economic content of commodity futures risk factors is our main interest in this paper, we expect that knowledge of the relations with future investment opportunities would contribute to a better understanding of commodity factors' predictive power for future economic growth. Our results provide rather weak but consistent evidence for the short-term predictors BM^{nb} and AVG^{nb}. The long-term predictors $MOM12^{nb}$, BM^{spr}, CR_H^{spr}, and SL^{spr} also show consistent and even stronger results in predicting future market returns and variance.

6. Further Analyses on Term Premia

Lastly, 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 robust predictability for future GDP growth, even after controlling for macroeconomic or equity risk factors. However, whether they subsume each other's predictability or which factor contains information for future economic states unique to other spreading factors has not yet been examined. In this section, we first conduct a horse race with spreading factors to answer these questions.

In Section 4, we find that three spreading factors, BM^{spr}, CR_H^{spr}, and SL^{spr}, show robust predictability for future GDP growth, and we therefore examine these. In addition, we include CR_L^{spr} and CV^{spr} in the set of predictors for comparison, since they comprise the other components, respectively, when we decompose the basis spreading factor and the basis-momentum spreading factor into two factors. Panel B of Table I exhibits considerable correlations among these spreading factors,[14] which implies that the inclusion of all these factors would negatively affect their respective predictive power, but we expect that it will be a more thorough test, from a conservative perspective, for determining 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 Equation (1). Model 1 in Table VIII includes no control variable (C_t), and Models 2 and 3 in Table VIII include control variables. As in Section 4.2, Model 2 includes macroeconomic factors, *TB*,

[14] For example, the correlation between BM^{spr} and SL^{spr} is 0.482 and that between BM^{spr} and CR_L^{spr} is 0.406.

TERM, *DEF*, and *CAY*, and Model 3 includes equity risk factors, *RMRF*, *SMB*, and *HML* as control variables.[15]

[Insert Table VIII about here]

First, Model 1 in Table VIII shows that only the slope spreading factor (SL^{spr}) has significant predictive power in the long term. Compared to the univariate results in Table II, our results show that all the factors have substantially reduced predictability. The factor SL^{spr} also shows a considerable decrease in predictability, but it still remains significant. For example, Table II shows that, for h = 4, …, 8, the coefficients on SL^{spr} have t-statistics from -3.79 to -2.83, while, in Model 1 of Table VIII, they range only from -2.13 to -1.67. However, the most notable finding from this horse race is that SL^{spr} is the only spreading factor that remains significant. In Model 2 in Table VIII, SL^{spr} shows further reduced predictability after controlling for macroeconomic factors. In fact, the coefficients on SL^{spr} appear to be significant only for h = 7 and h = 8. Though Model 2 shows the highly reduced predictive power of SL^{spr}, this predictor is still the only one that shows significant results. In Model 2, no factor, except SL^{spr}, shows significant results. Lastly, the results in Model 3 are in stark contrast to those in Model 2. After equity risk factors are controlled for, SL^{spr} shows significant results for all test horizons. Specifically, its predictive power appears to be lower and less significant for h = 1 (coeff. = -0.001, t-stat. = -1.89), but for all longer horizons, for h = 2, …, 8, the t-statistics on the coefficients are larger than 2.15 in absolute value. More

[15] Moreover, in Section 4.1, from the multivariate analyses, we find pairs of commodity futures factors that show 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 or equity factors. Since we control for macroeconomic or equity risk factors in Models 2 and 3 in Table 8, respectively, we expect that the joint effects can be also considered by including these control variables.

importantly, consistent with Models 1 and 2, only SL^{spr} shows significant predictive power among the tested spreading factors.

To summarize, our results from the horse race among the spreading factors indicate that the slope spreading factor is the strongest and most robust predictor. These results imply that the slope spreading factor subsumes the predictive power of the other spreading factors and contains information for future economic states distinct from that of the 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} between Models 2 and 3 of Table VIII is similar to that in the predictability of CR^{spr} in Panel B between Tables IV and V. In Tables IV and V, 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 VIII, the predictive power of SL^{spr} shows a 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 equity market–related risks seem to asymmetrically affect the long and short legs of CR^{spr}, and CR^{spr} more effectively captures the differences between the long and the short legs when the effects of equity risk factors are controlled for. Our results also suggest that CR^{spr} could act as a state variable jointly with equity risk factors.

Motivated by these previous findings and the similarity between SL^{spr} and CR^{spr}, we examine the long and short legs of the slope spreading factor as two independent factors.

Specifically, 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 future GDP growth, to investigate whether one of them mainly leads predictability or whether they symmetrically play a critical role in predicting 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 Equation (1), respectively. In Table IX, Models 1, 4, and 7 (Models 2, 5, and 8) have a high-slope (low-slope) spreading factor, and Models 3, 6, and 9 have both high- and low-slope spreading factors. In addition, for the control variables (C_t) in Equation (1), Models 1 to 3 include no control variables, and Models 4 to 6 (Models 7 to 9) include macroeconomic factors, *TB*, *TERM*, *DEF*, and *CAY* (equity risk factors, *RMRF*, *SMB*, and *HML*).

[Insert Table IX about here]

Interestingly, Table IX exhibits considerable differences in the predictability of SL_H^{spr} and SL_L^{spr}. First, without any control variables, Models 1 and 2 show that the predictive power of SL_H^{spr} is mainly concentrated in intermediate horizons, mainly for h = 3, …, 5, while that of SL_L^{spr} is mainly concentrated in longer horizons, for h = 6, …, 8. Model 3 shows that, in the multivariate case, the coefficients on SL_H^{spr} in the long term become 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 an adjusted R^2 value of 4.67%, while Models 1 and 3 report values of 0.50% and 5.35%, respectively.

After controlling for other effects, the effect of either the macroeconomic factors or the equity risk factors, we find that the coefficients on SL_H^{spr} show dramatic changes, whereas

those on SL_L^{spr} show only small differences. Specifically, after controlling for the macroeconomic factors, Models 4 and 6 present insignificant coefficients on SL_H^{spr} in all cases. By contrast, the long-term predictability of SL_L^{spr} remains significant, and the adjusted R^2 values for h = 7 and h = 8 also seem notable. In Panel B of Table IV, 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 VIII shows that, if the low-slope spreading factor is included instead of the slope spreading factor, it improves to 13.98%. Moreover, if the high- and low-slope spreading factors are included separately, Model 6 in Table VIII shows a small but further increase in the adjusted R^2 value, to 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 control variables are quite similar to those of SL^{spr} in Tables IV and V. We previously find that the predictive power of SL^{spr} becomes stronger after controlling for the equity factors (Table V), 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 IX additionally shows that robust long-term predictive power is observed for SL_L^{spr}, and the predictability of SL_H^{spr} appears to be highly sensitive to the control variables. Moreover, in the long term, SL_L^{spr} shows a larger adjusted R^2 value than SL_H^{spr} does. For example, in case of h = 8, Model 8 reports an adjusted R^2 value of 12.46% and Model 7 reports one of 10.08%.

Our results in Table IX suggest considerable differences between the long and short legs of the (change in) slope spreading factor as we find differences between the long and short legs

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 control variables. Moreover, in terms of the adjusted R^2 values, we find 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 short legs of the slope spreading factor play different roles in predicting future GDP growth.

7. Conclusion

This paper examines whether commodity futures risk factors can predict future GDP growth. Before controlling for other effects, we find that AVG^{nb} and BM^{nb} significantly predict future GDP growth in the short term, and $MOM12^{nb}$, BM^{spr}, CR_H^{spr}, and SL^{spr} predict it in the long term. However, after controlling for other effects, we find that only the long-term predicators 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 on nearby returns, before SRGN led 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 but more challenging to explain with 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 future GDP growth is subsumed by existing factors, either macroeconomic 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 among spreading factors shows 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 considered separately, 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 control variables. Moreover, in terms of the adjusted R^2 values, we find improved results when the model is extended to the model that includes the two legs, SL_H^{spr} and SL_L^{spr}, separately as independent variables. These results further imply that the long and 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 existing commodity futures risk factors following Liew and Vassalou's (2000) examination of equity risk factors, and the long and short legs of the slope spreading factor are therefore not among our main interests. However, though BP do not originally 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 work better jointly as state variables. Moreover, we expect this analysis to provide further implications for asset pricing studies in commodity futures markets. Vassalou (2003) constructs a factor that captures news related to future GDP growth using equity and fixed income portfolios and shows that this factor subsumes the cross-sectional pricing effects of *HML* and *SMB*. Therefore, if we determine a factor that is mainly driving the future GDP growth predictability of existing factors, then it could shed light on the asset pricing test, in that this factor even drives the cross-sectional pricing effects of the existing factors as well. We expect our findings to provide further implications in the asset pricing literature.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Data Citation

[Fama-French Three Factors] Fama, E.F. and French, K.R.; 1993; http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

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Table I. Summary statistics

This table presents the summary statistics (Panel A) of and correlations (Panel B) among the factors constructed by SRGN, BGR, and 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 six 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}), and (2) the nearby (spreading) return of the High4-minus-Low4 curvature portfolio, CV^{nb} (CV^{spr}). In addition, we 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 six 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}	$MOM12^{n}$	$MOM12^{s}$	$MOM6^{nb}$	$MOM6^{sp}$	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
$MOM12^{n}$	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
$MOM12^{s}$	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
$MOM6^{sp}$	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 II. Univariate regression

This table presents the results from the univariate predictive regressions. In Equation (1), F_t is each of the individual commodity futures risk factors denoted in the leftmost column and no control variables (C_t). The dependent variable is $GDP\ growth_{t+1Q,t+hQ}$, which is the GDP growth for the future h quarters, from quarter $t + 1Q$ to quarter $t + hQ$ for $h = 1, \ldots, 8$. For each regression, we report the coefficient on the commodity futures risk factor, its t-statistic (in parentheses), and the adjusted R^2 value. The t-statistics are computed using the Newey–West (1987) method with $2h$ 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 III. Multivariate regression

This table presents the results from the multivariate predictive regressions. In Equation (1), F_t is a set of commodity futures risk factors for each model, and no control variables (C_t). The dependent variable is $GDP\ growth_{t+1Q,t+hQ}$, which is the GDP growth for the future h quarters, from quarter t+ + 1Q to quarter $t + hQ$, for h = 1, …, 8. For each regression, we report the coefficient on the commodity futures risk factor, its t-statistic (in parentheses), and the adjusted R^2 value. The t-statistics are computed using the Newey–West (1987) method with 2h 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	0.020
		(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%

Table IV. Predictability after controlling for macroeconomic factors

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

Panel A: Predictability of macroeconomic factors									
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 factors

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%
AVG^{spr}	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%
$MOM12^{nb}$	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%
$MOM12^{spr}$	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%
$MOM6^{nb}$	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%
$MOM6^{spr}$	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%
SL^{nb}	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%
SL^{spr}	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%
CV^{nb}	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%
CV^{spr}	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 V. Predictability after controlling for equity risk factors

This table presents the predictive regressions including equity risk factors. In Equation (1), F_t is each of the individual commodity futures risk factors and C_t is a set of equity risk factors. For the 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 the future h quarters, from quarter $t + 1Q$ to quarter $t + hQ$, for $h = 1, \ldots, 8$. For each regression, we report the coefficient on the commodity futures risk factor, its t-statistics (in parentheses), and the adjusted R^2 value. The t-statistics are computed using the Newey–West (1987) method with $2h$ 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)
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)
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	12.61%	13.99%	13.75%	13.38%	12.19%	10.79%	9.02%	8.06%

Panel B: Univariate regression controlling for equity risk factors

Variable		Horizon (h)							
		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%
$MOM6^{nb}$	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%
$MOM6^{spr}$	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%
SL^{nb}	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%
SL^{spr}	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%
CV^{nb}	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%
CV^{spr}	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 VI. Predictability for future market returns

This table presents the predictive multivariate regressions for future market returns. We test BM^{nb}, BM^{spr}, CR_H^{spr}, AVG^{nb}, $MOM12^{nb}$, and SL^{spr} as F_t in Equation (2). Panel A includes no control variable (C_t), and Panels B and C include control variables. For each regression, we report the coefficient on the commodity futures risk factors, their t-statistics (in parentheses), and the adjusted R^2 value. The *t*-statistics are computed using the Newey–West (1987) method with 2*h* lags. The sample period is from 1982:1Q to 2017:3Q.

Panel A: Univariate regression									
Variable		Horizon (*h*)							
		1	2	3	4	5	6	7	8
BM^{nb}	Coefficient	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	0.000	0.000
	(t-stat.)	(-1.35)	(-3.01)	(-2.70)	(-2.72)	(-3.04)	(-2.72)	(-2.30)	(-1.88)
	adj. R^2	0.88%	3.90%	5.14%	4.66%	5.45%	3.81%	2.11%	2.30%
BM^{spr}	Coefficient	-0.006	-0.005	-0.006	-0.005	-0.003	-0.003	-0.002	-0.002
	(t-stat.)	(-2.25)	(-2.89)	(-3.50)	(-3.19)	(-2.32)	(-2.32)	(-2.25)	(-2.13)
	adj. R^2	3.94%	5.66%	9.92%	10.02%	5.97%	4.51%	2.71%	1.87%
CR_H^{spr}	Coefficient	0.001	0.005	0.005	0.005	0.005	0.003	0.002	0.001
	(t-stat.)	(0.24)	(1.96)	(1.90)	(2.09)	(2.29)	(1.72)	(1.41)	(0.88)
	adj. R^2	-0.72%	1.90%	2.14%	4.19%	4.22%	1.21%	0.21%	-0.34%
AVG^{nb}	Coefficient	0.002	0.000	-0.001	-0.001	-0.001	-0.001	0.000	-0.001
	(t-stat.)	(1.10)	(-0.30)	(-1.87)	(-2.78)	(-1.91)	(-1.67)	(-1.78)	(-2.14)
	adj. R^2	0.80%	-0.66%	0.84%	1.54%	0.68%	0.47%	0.08%	0.79%
$MOM12^{nb}$	Coefficient	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	0.000	0.000
	(t-stat.)	(-1.89)	(-1.67)	(-2.29)	(-1.98)	(-1.80)	(-1.89)	(-1.34)	(-1.01)
	adj. R^2	1.34%	1.11%	5.96%	4.63%	3.41%	2.62%	1.00%	0.71%
SL^{spr}	Coefficient	-0.001	-0.001	-0.003	-0.003	-0.002	-0.002	-0.001	-0.001
	(t-stat.)	(-0.32)	(-0.64)	(-1.84)	(-1.54)	(-1.31)	(-1.26)	(-1.64)	(-1.37)
	adj. R^2	-0.66%	-0.34%	2.59%	2.79%	2.27%	1.39%	1.39%	0.48%

Panel B: Univariate regression controlling for macroeconomic factors	
Variable	Horizon (*h*)

		1	2	3	4	5	6	7	8
BM^{nb}	Coefficient	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	0.000	0.000
	(t-stat.)	(-1.30)	(-2.59)	(-2.34)	(-2.36)	(-2.90)	(-2.46)	(-2.19)	(-1.93)
	adj. R^2	-1.53%	2.35%	4.85%	4.14%	5.59%	6.15%	8.28%	12.52%
BM^{spr}	Coefficient	-0.006	-0.006	-0.006	-0.005	-0.003	-0.002	-0.002	-0.001
	(t-stat.)	(-2.17)	(-2.72)	(-3.39)	(-3.22)	(-2.42)	(-2.04)	(-1.69)	(-1.36)
	adj. R^2	1.71%	4.77%	10.66%	10.11%	6.01%	6.31%	8.36%	11.72%
CR_H^{spr}	Coefficient	0.001	0.006	0.005	0.006	0.005	0.003	0.002	0.001
	(t-stat.)	(0.31)	(2.12)	(2.18)	(2.23)	(2.47)	(1.74)	(1.39)	(0.93)
	adj. R^2	-2.87%	1.30%	2.96%	4.84%	5.38%	4.55%	7.44%	11.16%
AVG^{nb}	Coefficient	0.002	0.000	-0.001	-0.001	-0.001	-0.001	0.000	-0.001
	(t-stat.)	(1.27)	(0.02)	(-1.18)	(-2.16)	(-1.65)	(-1.35)	(-1.18)	(-1.66)
	adj. R^2	-0.52%	-1.98%	0.10%	0.69%	0.74%	3.52%	7.12%	12.19%
$MOM12^{nb}$	Coefficient	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	0.000	0.000
	(t-stat.)	(-1.94)	(-1.43)	(-2.18)	(-1.93)	(-1.76)	(-1.87)	(-1.35)	(-1.09)
	adj. R^2	-0.99%	-0.36%	5.77%	4.31%	3.83%	5.62%	7.72%	11.66%
SL^{spr}	Coefficient	-0.001	-0.001	-0.003	-0.003	-0.002	-0.002	-0.001	-0.001
	(t-stat.)	(-0.33)	(-0.73)	(-1.99)	(-1.63)	(-1.34)	(-1.23)	(-1.50)	(-1.04)
	adj. R^2	-2.81%	-1.43%	3.15%	2.74%	2.53%	4.12%	7.90%	11.42%

Panel C: Univariate regression controlling for equity risk factors

Variable		Horizon (h)							
		1	2	3	4	5	6	7	8
BM^{nb}	Coefficient	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	0.000	0.000
	(t-stat.)	(-1.29)	(-3.00)	(-2.88)	(-3.07)	(-3.47)	(-2.87)	(-2.49)	(-2.00)
	adj. R^2	1.97%	5.58%	8.29%	10.77%	12.87%	10.54%	6.65%	4.97%
BM^{spr}	Coefficient	-0.006	-0.005	-0.005	-0.005	-0.003	-0.002	-0.002	-0.001
	(t-stat.)	(-2.15)	(-2.71)	(-3.58)	(-3.41)	(-2.39)	(-2.28)	(-2.05)	(-1.88)
	adj. R^2	4.84%	6.90%	12.41%	15.04%	12.42%	10.33%	6.48%	3.96%
CR_H^{spr}	Coefficient	0.000	0.005	0.004	0.005	0.004	0.002	0.001	0.001

	(t-stat.)	(0.06)	(1.90)	(1.85)	(2.02)	(2.31)	(1.77)	(1.29)	(0.74)
	adj. R^2	0.52%	3.41%	4.97%	9.78%	11.22%	7.74%	4.47%	2.14%
AVG^{nb}	Coefficient	0.002	0.000	-0.001	-0.001	-0.001	-0.001	0.000	-0.001
	(t-stat.)	(1.22)	(-0.31)	(-1.69)	(-2.36)	(-1.57)	(-1.61)	(-1.45)	(-1.92)
	adj. R^2	2.15%	1.20%	3.93%	7.67%	8.49%	7.55%	4.45%	3.23%
$MOM12^{nb}$	Coefficient	-0.001	-0.001	-0.001	-0.001	-0.001	0.000	0.000	0.000
	(t-stat.)	(-2.00)	(-1.55)	(-2.23)	(-1.88)	(-1.68)	(-1.77)	(-1.22)	(-0.91)
	adj. R^2	2.54%	2.83%	8.87%	10.45%	10.74%	9.25%	5.22%	3.10%
SL^{spr}	Coefficient	-0.001	-0.001	-0.003	-0.002	-0.002	-0.002	-0.001	-0.001
	(t-stat.)	(-0.32)	(-0.60)	(-1.86)	(-1.56)	(-1.36)	(-1.34)	(-1.67)	(-1.29)
	adj. R^2	0.60%	1.45%	5.52%	8.57%	9.61%	8.07%	5.48%	2.83%

Table VII. Predictability for future market variance

This table presents the predictive multivariate regressions for future market variance. We test BM^{nb}, BM^{spr}, CR_H^{spr}, AVG^{nb}, $MOM12^{nb}$, and SL^{spr} as F_t in Equation (3). Panel A includes no control variable (C_t), and Panels B and C include control variables. For each regression, we report the coefficient on the commodity futures risk factors, their t-statistics (in parentheses), and the adjusted R^2 value of the regression. The *t*-statistics are computed using the Newey–and West (1987) method with 2*h* lags. The sample period is from 1982:1Q to 2017:3Q.

Panel A: Univariate regression									
Variable		Horizon (*h*)							
		1	2	3	4	5	6	7	8
BM^{nb}	Coefficient	-0.006	0.013	0.029	0.038	0.041	0.045	0.037	0.035
	(t-stat.)	(-0.46)	(0.80)	(1.40)	(1.55)	(1.62)	(1.54)	(1.14)	(0.88)
	adj. R^2	-0.49%	-0.25%	0.61%	0.82%	0.68%	0.54%	0.03%	-0.14%
BM^{spr}	Coefficient	0.009	0.054	0.119	0.154	0.185	0.188	0.199	0.199
	(t-stat.)	(0.14)	(0.67)	(1.56)	(1.81)	(1.69)	(1.52)	(1.51)	(1.39)
	adj. R^2	-0.71%	-0.17%	0.81%	1.03%	1.15%	0.73%	0.69%	0.56%
CR_H^{spr}	Coefficient	-0.025	-0.089	-0.264	-0.388	-0.490	-0.471	-0.429	-0.440
	(t-stat.)	(-0.88)	(-1.26)	(-2.23)	(-1.92)	(-1.88)	(-1.71)	(-1.44)	(-1.44)
	adj. R^2	-0.62%	-0.13%	2.27%	3.67%	4.53%	3.05%	1.98%	1.88%
AVG^{nb}	Coefficient	-0.070	-0.053	-0.030	-0.009	0.015	0.011	-0.007	-0.003
	(t-stat.)	(-1.55)	(-0.97)	(-0.53)	(-0.17)	(0.27)	(0.20)	(-0.15)	(-0.06)
	adj. R^2	11.95%	1.85%	-0.26%	-0.72%	-0.69%	-0.73%	-0.75%	-0.76%
$MOM12^{nb}$	Coefficient	-0.009	0.006	0.031	0.043	0.053	0.047	0.035	0.033
	(t-stat.)	(-0.69)	(0.36)	(1.52)	(1.67)	(1.59)	(1.49)	(1.14)	(1.06)
	adj. R^2	0.14%	-0.63%	1.19%	1.81%	2.10%	1.03%	0.09%	-0.09%
SL^{spr}	Coefficient	-0.011	-0.045	0.066	0.174	0.251	0.274	0.298	0.322
	(t-stat.)	(-0.26)	(-0.71)	(1.05)	(1.86)	(1.73)	(1.71)	(1.88)	(1.99)
	adj. R^2	-0.67%	-0.30%	-0.21%	1.79%	3.19%	2.96%	3.02%	3.23%

Panel B: Univariate regression controlling for macroeconomic factors	
Variable	Horizon (*h*)

		1	2	3	4	5	6	7	8
BM^{nb}	Coefficient	0.004	0.030	0.052	0.067	0.076	0.081	0.076	0.073
	(t-stat.)	(0.55)	(1.77)	(1.99)	(2.12)	(2.40)	(2.47)	(2.22)	(1.84)
	adj. R^2	10.81%	10.67%	12.66%	13.60%	13.44%	13.23%	13.33%	13.20%
BM^{spr}	Coefficient	0.016	0.065	0.135	0.176	0.211	0.215	0.228	0.229
	(t-stat.)	(0.31)	(0.88)	(1.94)	(2.14)	(1.95)	(1.87)	(1.89)	(1.76)
	adj. R^2	10.84%	9.05%	10.32%	11.03%	11.34%	11.06%	12.12%	12.27%
CR_H^{spr}	Coefficient	-0.005	-0.062	-0.233	-0.357	-0.464	-0.449	-0.406	-0.421
	(t-stat.)	(-0.14)	(-0.78)	(-2.00)	(-1.85)	(-1.82)	(-1.70)	(-1.44)	(-1.45)
	adj. R^2	10.70%	8.53%	10.72%	12.54%	13.69%	12.68%	12.76%	13.03%
AVG^{nb}	Coefficient	-0.058	-0.031	0.005	0.040	0.076	0.079	0.065	0.072
	(t-stat.)	(-1.58)	(-0.72)	(0.10)	(0.87)	(1.45)	(1.47)	(1.34)	(1.48)
	adj. R^2	19.00%	9.06%	8.35%	9.28%	10.34%	10.39%	10.98%	11.39%
$MOM12^{nb}$	Coefficient	-0.003	0.018	0.049	0.067	0.080	0.077	0.065	0.063
	(t-stat.)	(-0.34)	(1.73)	(2.18)	(1.95)	(1.85)	(1.90)	(1.70)	(1.62)
	adj. R^2	10.78%	9.30%	13.05%	14.64%	15.30%	13.75%	13.14%	13.02%
SL^{spr}	Coefficient	-0.020	-0.061	0.046	0.149	0.221	0.238	0.256	0.278
	(t-stat.)	(-0.47)	(-0.97)	(0.82)	(1.81)	(1.68)	(1.66)	(1.86)	(1.91)
	adj. R^2	10.95%	9.06%	8.60%	10.62%	11.97%	11.98%	13.06%	13.56%

Panel C: Univariate regression controlling for equity risk factors

Variable		Horizon (h)							
		1	2	3	4	5	6	7	8
BM^{nb}	Coefficient	-0.008	0.010	0.024	0.033	0.037	0.039	0.033	0.032
	(t-stat.)	(-0.71)	(0.65)	(1.34)	(1.60)	(1.75)	(1.63)	(1.19)	(0.95)
	adj. R^2	8.27%	8.92%	8.78%	9.04%	9.75%	9.19%	7.25%	5.65%
BM^{spr}	Coefficient	-0.003	0.030	0.088	0.115	0.137	0.131	0.142	0.142
	(t-stat.)	(-0.06)	(0.36)	(1.15)	(1.49)	(1.43)	(1.16)	(1.11)	(1.04)
	adj. R^2	7.75%	8.83%	8.64%	8.79%	9.67%	8.89%	7.37%	5.79%
CR_H^{spr}	Coefficient	-0.018	-0.079	-0.248	-0.372	-0.476	-0.455	-0.414	-0.428

	(t-stat.)	(-0.56)	(-1.01)	(-2.25)	(-1.87)	(-1.79)	(-1.60)	(-1.33)	(-1.35)
	adj. R^2	7.81%	9.13%	10.50%	11.94%	13.69%	11.78%	9.21%	7.66%
AVG^{nb}	Coefficient	-0.062	-0.035	-0.007	0.021	0.054	0.053	0.033	0.034
	(t-stat.)	(-1.50)	(-0.73)	(-0.14)	(0.43)	(1.03)	(0.96)	(0.62)	(0.60)
	adj. R^2	17.31%	9.71%	7.80%	7.96%	9.38%	8.73%	6.81%	5.29%
$MOM12^{nb}$	Coefficient	-0.009	0.006	0.032	0.044	0.053	0.048	0.035	0.032
	(t-stat.)	(-0.78)	(0.48)	(1.74)	(1.82)	(1.70)	(1.63)	(1.23)	(1.10)
	adj. R^2	8.56%	8.79%	9.80%	10.43%	11.56%	9.99%	7.47%	5.75%
SL^{spr}	Coefficient	-0.005	-0.038	0.075	0.183	0.262	0.284	0.305	0.327
	(t-stat.)	(-0.13)	(-0.67)	(1.34)	(2.03)	(1.84)	(1.80)	(1.92)	(1.95)
	adj. R^2	7.76%	8.96%	8.49%	10.65%	12.96%	12.21%	10.63%	9.29%

Table VIII. Horse race with spreading factors

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

This table shows the predictability of the high- and low-slope spreading factors (SL_H^{spr} and SL_L^{spr}, respectively). We consider three models, one including the high-slope spreading factor, one the low-slope spreading factor, and one both the high- and low-slope spreading factors as F_t in Equation (1), respectively. Models 1, 4, and 7 (Models 2, 5, an 8) have a high-slope (low-slope) spreading factor, and Models 3, 6, and 9 have both high- and low-slope spreading factors. In addition, for the control variables (C_t) in Equation (1), Models 1 to 3 include no control variables, and Models 4 to 6 (Models 7 to 9) include the 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 (in parentheses), and the adjusted R^2 value. The t-statistics are computed using the Newey–West (1987) method with 2*h* 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%

Table AI. Correlations with control variables

This table presents the correlations among the commodity futures risk factors and the other control variables. The macroeconomic factors include the short-term interest rate (*TB*), the term spread (*TERM*), the default spread (*DEF*), and the variable *CAY* of Lettau and Ludvigson (2000). Specifically, we use the three-month Treasury bill rate for *TB*, the yield spread between 10-year and one-year government bonds for *TERM*, and the yield spread between Moody's BAA and AAA corporate bonds for *DEF*. The variable *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
BM^{nb}	-0.051	0.019	0.008	0.196	-0.214	-0.009	0.046
BM^{spr}	-0.031	0.020	-0.098	0.114	0.005	-0.002	-0.062
CR^{nb}	0.031	-0.088	-0.120	0.033	-0.037	-0.099	0.142
CR^{spr}	-0.025	-0.059	-0.030	0.064	-0.152	-0.040	0.079
CR_H^{spr}	-0.012	-0.065	0.012	-0.061	-0.063	-0.026	-0.057
CR_L^{spr}	0.022	0.030	0.047	-0.113	0.139	0.031	-0.130
AVG^{nb}	0.215	0.117	0.046	-0.037	-0.191	0.108	-0.056
AVG^{spr}	0.024	-0.061	0.001	-0.036	0.067	-0.046	-0.086
$MOM12^{nb}$	0.045	0.038	-0.028	0.140	-0.195	0.021	0.082
$MOM12^{spr}$	0.066	0.065	-0.024	0.166	0.034	0.005	0.029
$MOM6^{nb}$	0.098	0.080	-0.082	0.062	-0.026	0.002	0.035
$MOM6^{spr}$	0.135	0.143	-0.077	0.118	0.067	-0.019	-0.009
SL^{nb}	0.021	0.024	0.016	0.043	-0.018	-0.063	0.002
SL^{spr}	0.088	0.045	-0.047	0.062	0.072	-0.053	-0.024
CV^{nb}	-0.108	-0.068	-0.009	0.159	-0.178	0.018	0.097
CV^{spr}	-0.015	0.063	-0.049	0.063	0.000	0.070	-0.128