Commodity Return Predictability *

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ABSTRACT

The futures curve of an aggregate commodity portfolio is time-varying and changes from upward (contango) to downward sloping (backwardation) which implies negative or positive expected returns. The basis arises as a natural fundamental to predict commodity returns. However, the empirical evidence on the aggregate portfolio level is very weak. I construct a factor based on different forward rates along the futures curve and find that commodity returns are predictable. Economic fundamentals, such as industrial production or global trade, positively predict aggregate commodity returns and used jointly with this forward rates factor significantly improve overall predictability in- and out-of-sample. I find evidence that expected aggregate commodity returns are procyclical. When economic activity is high, the commodity yield curve tends to be inverted and expected returns are high.

Keywords: Commodities, Return Predictability, Economic Fundamentals
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I. Introduction

Expected returns of an aggregate commodity portfolio are driven by the shape of the underlying commodity yield curve which relates the current futures price to the spot price and the remaining time to maturity. The futures curve changes from upward (contango) to downward sloping (backwardation) which implies negative or positive expected returns on commodity futures. Figure 1 shows the significant extent to which the futures curve of an aggregate commodity portfolio is time-varying. At the end of December 2008 the average futures price was increasing with maturity and higher than the average spot price across 32 different commodities implying an upward sloping yield curve (or contango). Conversely, at the end of April 2014 the commodity yield curve was inverted (or in backwardation) which refers to a situation when average futures prices are lower than the spot price. Interestingly, when looking at the economic activity around these two dates, one finds that December 2008 was marked as a recession and April 2014 as an expansionary period by the NBER business cycle dating.[1] Further, the 12-month growth rate of world industrial production was -11.16 % and 3.27 % respectively.

[Figure 1 about here.]

My main contribution is to show that aggregate commodity returns are predictable, both in- and out-of-sample, using factors directly derived from the yield curve of an aggregate commodity portfolio. Further, I find that the shape of the aggregate yield curve is strongly related to economic activity and thus, I argue that expected commodity returns are procyclical. In contrast to existing studies investigating individual commodity markets,[2] I focus on the predictability of aggregate returns similar to tradable commodity indices such as the SP-GSCI. Hong and Yogo (2012) concentrate on the predictive power of futures' markets open interest for aggregate commodity returns and Gargano and Timmermann (2014) only investigate the predictability of aggregate spot returns. Szymanowska, de Roon, Nijman, and van den Goorbergh (2014) document the existence of spot and term risk premia in commodity futures returns. However, they do not predict aggregate returns, but instead aim to price different commodity risk factors. I contribute to the literature by explicitly using information of the term structure of futures prices to predict aggregate commodity returns and further relating it to economic fundamentals.

[1] For further information on NBER business cycle dates see `http://www.nber.org/cycles.html`

[2] Gorton, Hayashi, and Rouwenhorst (2012) provide a good overview of individual commodity yield factors and empirically test their predictability for commodity returns.

First, this paper examines whether returns of an aggregate commodity portfolio are predictable. No arbitrage implies that in contango (backwardation) futures prices are expected to decrease (increase) and the roll yield is negative (positive). However, the main point is how to best model the aggregate commodity yield curve and in particular its time-variation in order to forecast future commodity returns. The basis, i.e. the difference between the current futures and spot price, arises as a natural fundamental to predict returns on commodity futures. However, the corresponding empirical evidence is very weak. I construct a factor which uses information along the whole commodity futures curve. This forward rates factor significantly predicts commodity futures returns across maturities and horizons. Further, I apply a principal component analysis to the commodity basis of different maturities and I identify three factors which correspond to the level, slope and curvature of the commodity yield curve. In particular, the curvature factor significantly predicts commodity futures returns.

Second, this paper investigates how aggregate commodity returns relate to economic fundamentals. The focus is on rationalizing the time-variation of the commodity yield curve. I document that economic fundamentals positively predict aggregate commodity futures returns and using them jointly with these yield curve factors significantly raises overall predictability in- and out-of-sample. Moreover, I find evidence that expected returns on commodity futures are procyclical. When economic activity is high, the commodity yield curve tends to be inverted and expected commodity returns are high. Hence, economic activity seems to be an important determinant of an aggregate commodity portfolio's yield curve.

I argue that the procyclical nature of expected commodity returns is driven by the time-variation in industrial production where commodities are needed as production inputs. That is, higher economic activity increases the demand for commodities as production inputs, which in turn raises the spot price and reduces existing inventories. As a result, the commodity yield curve gets inverted (backwardation) and expected returns on commodity futures are high and positive. Conversely, a decrease in economic activity implies low expected commodity returns due to a decrease in commodity demand and a fall in spot prices. Moreover, the analysis of commodity sector returns shows that returns of commodities which are demanded as production inputs are very sensitive to economic activity, whereas other commodities which are rather relevant for food than industrial production are less affected by current economic conditions. These characteristics translate to cross-sectional differences in marginal effects when using economic fundamentals to predict future commodity sector returns.

This paper is structured as follows. Section II discusses different theories about the commodity yield curve and their implications for return predictability. Section III describes the commodity futures market data and the construction of the key predictor variables. In Section IV, I present the main empirical results on the predictability of aggregate commodity returns as well as their relation to economic fundamentals. Section V encompasses further empirical robustness analysis and Section VI presents results on the predictability of commodity sector returns. Section VII concludes.

II. Literature Review

The theory of storage states that the commodity futures price is a function of spot price, storage costs and convenience yield (Working (1933), Kaldor (1939), Brennan (1958)).[3] It is derived from the cost-of-carry model and the no-arbitrage condition to price a commodity futures contract. This theory postulates that commodity inventories react to changes in commodity supply and determine the shape of the futures curve. For example, in times of a commodity supply surplus the spot price will decrease and inventories build up which implies that the storage costs exceed the convenience yield. As a result the futures price will be higher than the spot price and the futures curve upward sloping (contango). Conversely, a supply shortage will decrease inventories and lead to an inverted futures curve (backwardation). Gorton, Hayashi, and Rouwenhorst (2012) find empirical evidence that the level of physical inventories predict commodity futures returns. Further, they show that the basis reflects the state of inventories and thus also predicts returns.

In fact, the basis arises as a natural predictor for (individual) commodity returns. Fama and French (1987) run classical regressions where they use the forward-spot spread, i.e. the basis, to predict either futures returns or spot price changes. The empirical evidence for time-varying expected returns depends on the type of commodity: it is strong for agriculturals and weak for metals. Alternatively, Erb and Harvey (2006) and Fuertes, Miffre, and Rallis (2010) show that a portfolio trading strategy which sorts on the basis—going long backwardated commodities and

[3]The convenience yield is the benefit one earns from physically holding the commodity to avoid stockouts or production disruptions.

shorting the ones in contango—can generate significant abnormal returns. In a similar vein, Szymanowska, de Roon, Nijman, and van den Goorbergh (2014) find that the basis spread is a significant risk factor which prices the cross-section of commodity returns. Yang (2013) shows that investment shocks can explain the basis spread and thus provides a macroeconomic risk-based explanation. Regarding the question of time-variation in the commodity yield curve, Bailey and Chan (1993) identify idiosyncratic and common factors in the variability of the basis whose relative importance depends on a commodity's storability. They argue that macroeconomic fundamentals cause common basis variability across different commodity markets.

According to the theory of normal backwardation commodity futures are used by hedgers to transfer the price risk to speculators (Keynes (1930), Hicks (1939), Cootner (1960)). The inequality between short and long position of hedgers, which is known as hedging pressure, requires the intervention of speculators to restore equilibrium in the futures market and hence, they demand a risk premium as compensation. This theory postulates that the hedging pressure of commodity producers and consumers determines the shape of the futures curve. For example, if hedgers are net short, speculators must be net long. Since the latter demand positive expected returns on their long positions, the futures price will be lower than the spot price and the commodity market is in backwardation. Conversely, if hedgers are net long, speculators will demand positive returns on their short positions which implies an upward sloping futures curve (contango). Empirically the hedging pressure can predict returns on individual (mostly agricultural) commodity futures (Chang (1985), Bessembinder (1992), de Roon, Nijman, and Veld (2000)).

These theories focus on futures prices of individual commodities and the resulting characteristics can explain the cross-sectional differences in commodity returns. However, it is not obvious how these individual yield factors affect the futures curve and returns on an aggregate commodity portfolio.[4] Idiosyncratic effects probably average out and the focus of this paper is on common time-series variation instead of cross-sectional heterogeneity. In a similar vein, Hong and Yogo (2012) show that open interest in futures markets is a better predictor for aggregate returns than the hedging pressure or the basis, which holds true for different asset classes. They argue that open interest contains information about future economic activity which is not fully revealed by

[4]For example, the role of inventories is different for perishable or non-perishable commodities. While perishable goods cannot be stored and have a high convenience yield, non-perishable commodities will cause higher storage costs. Similarly, the hedging pressure for agriculturals will be strongly influenced by seasonality or wheather risk, whereas these factors are less important for commodities that can be produced throughout the year.

prices alone, since asset prices initially underreact to macroeconomic news. In line with the results in this paper, they find that expected commodity returns are procyclical. However, Hong and Yogo (2012) do not relate their results to the term structure of futures prices. Open interest is a transaction quantity which might not contain the same information as an aggregate yield curve.

Furthermore, there is little evidence how economic fundamentals, such as global trade or industrial production, affect the time-series variation in aggregate commodity returns. Gargano and Timmermann (2014) use some macroeconomic variables to predict commodity spot returns. However, their focus is more on out-of-sample predictability and multivariate approaches, rather than on rationalizing the cyclical properties of aggregate commodity futures returns. Still, the relation of commodity returns to economic fundamentals might be important for producers who want to hedge future price risk, as well as financial investors who expect positive returns on their commodity portfolios. In this vein, the objective of this paper is to understand how a sudden decrease in global trade or industrial production affects the average pricing of commodities.

III. Data and Variable Definitions

The aggregate commodity portfolio consists of 32 different commodities spread across 5 sectors (Energy, Grains and Oilseeds, Livestock, Metals, Softs) and covers a broad commodity market universe. For each commodity, I collect daily settlement prices of all individual futures contracts available on Bloomberg. I select only liquid contracts by neglecting those contracts with zero trading volume for at least one year prior to expiration. Table I lists all commodities grouped by sector together with the exchange on which they are traded, the corresponding Bloomberg ticker symbol, the year of the first recorded observation and the delivery months used. The data set is comparable to the ones used by Gorton, Hayashi, and Rouwenhorst (2012), Hong and Yogo (2012) and Szymanowska, de Roon, Nijman, and van den Goorbergh (2014). I choose January 1975 as the starting date since price data for nearly half of the 32 commodities is available from this date onwards. The sample period ends in August 2015.

Data on open interest, i.e. the quantity of futures contracts outstanding, as well as long and short positions of commercial traders (hedgers) for each futures contract is published in the Commitment of Traders reports issued by the Commodity Futures Trading Commission (CFTC). The corresponding CFTC codes for each individual commodity are listed in the last column of Table I.

Note that the CFTC data starts in January 1986. Further, I use data on trading volume for each commodity futures contract which is also taken from Bloomberg. As proxies for economic fundamentals I use monthly OECD aggregate data for industrial production, total exports and imports as well as the composite leading indicator and business confidence index.[5] Since commodities are traded worldwide, I choose OECD aggregate variables instead of macroeconomic variables for individual countries. Data on economic fundamentals is from the OECD database and starts in January 1975, except for data on exports and imports which is only available since January 1980.

A. *Commodity returns*

The h-month return of a fully collateralized long position in a commodity futures contract with maturity T in excess of the risk-free rate is

$$rx_{t+h}^{(n)} = \frac{F_{t+h,T} - F_{t,T}}{F_{t,T}} \tag{1}$$

where $F_{t,T}$ is the futures price at the end of month t which matures at the end of month T. I assume that at time t, $F_{t,T}$ is invested as collateral at the risk-free rate and hence, the futures position is fully collateralized. Individual futures contracts are rolled over to the next maturity contract $n = T - t$ months before delivery. The roll-over is done end of month and prices are backwards ratio adjusted. To analyze the term structure of returns, I calculate returns with different times to maturity and use $n = 1, 2, 3, 4$ months before delivery to roll over each contract to the next nearest contract. Further, I calculate returns over various holding periods, where $h = 1, 3, 6, 9, 12$ months, to analyze the effect of different forecasting horizons.

First, I calculate h-month returns with maturity n, $rx_{t+h}^{(n)}$, for each individual commodity. Second, I calculate an equal weighted average return within each sector and third, I equal weight each sector return to obtain the return on an aggregate commodity futures portfolio. As a result no sector will dominate even if the number of commodities within each sector varies over time. Panel A of Table II reports summary statistics for the 1-month aggregate commodity returns across different maturities. The average monthly excess return of this aggregate commodity portfolio is nearly 30 basis points with a monthly volatility of well over 3 %. Moreover, these returns are

[5]The OECD composite leading indicator aggregates various economic variables of all OECD countries and is constructed to anticipate economic turning points around 6 to 9 months ahead.

negatively skewed, have a kurtosis of over 5 and very low first-order autocorrelations. Overall, there is little unconditional variation between returns of different maturities. In addition to the statistics reported in Table II, the correlation between these monthly aggregate commodity returns and the SP-GSCI index returns is 0.8, and 0.92 with the DJ-UBS commodity index, respectively.

B. *Predictor variables*

The predictor variables are divided into three groups. The first group consists of commodity fundamentals which directly relate to the futures curve. The second group comprises additional commodity-specific variables such as hedging pressure or open interest growth in the futures market. The third group contains economic fundamentals.

B.1. *Commodity fundamentals*

The basis or forward-spot spread relates the current futures price to the spot price. The n-month basis of a commodity future is given by

$$basis_t^{(n)} = \left(\frac{F_{t,T}}{S_t}\right)^{\frac{1}{(T-t)}} - 1 \tag{2}$$

where $n = T - t = 1, 2, 3, 4$ months before delivery. For the spot price S_t, I use the nearest-to-maturity futures contract. The basis is positive if the commodity market is in contango (upward sloping yield curve) and negative in times of backwardation (downward sloping yield curve).

Alternatively, the forward rate relates two futures prices with different maturities. The n-month forward rate of a commodity future is defined as

$$forward_t^{(n)} = \left(\frac{F_{t,T}}{F_{t,T-1}}\right) - 1 \tag{3}$$

where $forward_t^{(1)} = basis_t^{(1)}$ holds and $n = T - t = 1, 2, 3, 4$ months before delivery. For longer maturities, the forward rate corresponds to a linear interpolation of the futures curve.

First, I calculate the basis and forward rates for each individual commodity and for different maturities, with $n = 1, 2, 3, 4$ months to delivery. To aggregate within sectors I use the median basis and median forward rates, which is less sensitive to outliers. Across sectors I compute equally weighted averages of sector basis and sector forward rates, similar to Hong and Yogo

(2012). Panel A of Table II also reports summary statistics for the aggregate commodity basis and forward rates across different maturities. The average basis over the whole sample period from 1975 to 2015 is positive which implies that the commodity market was on average in contango. However, the basis volatility indicates quite some time-series variation. Overall, the basis and forward rates across different maturities seem to be highly correlated since there is little variation across the unconditional moments. Figure 2 shows a time-series plot of the aggregate commodity basis with maturity 1 and 4 months. At first glance, there is a substantial amount of variation both across time and across maturities with some significant spikes. In general, the basis tends to be in contango during turbulent economic times, such as the oil crises in the late 1970s or the recent financial crisis.

[Figure 2 about here.]

To explain common time-series variation in the term structure of the aggregate commodity basis, I apply a principal component analysis to the basis of different maturities. The first three principal component factors explain nearly 99 % of basis variation.[6] Figure 3 shows the loadings of each individual PC factor. Obviously, the first factor captures the average level of the basis across maturities. The second factor negatively loads on the short-end and positively on the long-end of the commodity yield curve and thus, represents the slope of the futures curve. The third factor is dominated by the negative loading of the 2-month basis which seems to drive the curvature of the commodity yield curve. The fourth PC factor is rather irrelevant in explaining basis variation.

[Figure 3 about here.]

B.2. Additional predictors

Besides commodity fundamentals, there are other variables known to predict commodity returns. First, I calculate the volatility of commodity returns as the standard deviation of daily returns over the past 12 months. Second, I use commodity spot price changes which are equal to futures returns at expiration, i.e. with zero months to maturity. For both variables, the return volatility as well as spot price changes, I first equally weight within each sector and then, equally weight across sectors to get aggregate versions of each variable.

[6]The first PC factor explains 84 %, the second 11 % and the third about 4 % of basis variation.

Hedging pressure is a measure of supply and demand imbalances in the commodity futures market. It is defined as the ratio of the difference between the number of short and long hedge positions held by commercial traders relative to the total number of hedge positions held by commercial traders in a specific commodity futures market. To aggregate within each sector, I sum all individual short and long positions across all commodities in that sector and calculate the sector hedging pressure. Then I compute the aggregate commodity market hedging pressure as an equally weighted average of sector hedging pressures, similar to Hong and Yogo (2012).

Open interest in a specific commodity market is defined as the total number of futures contracts outstanding. Similarly, trading volume is defined as the total number of futures contracts traded on a day and in a specific commodity market. For both variables, I first aggregate within each sector by summing the total number of futures (outstanding or traded) across all commodities in that sector. Next, I calculate monthly growth rates of sector open interest and sector volume. Finally, the aggregate growth rate of commodity market open interest or volume is an equally weighted average of growth rates for each sector. Following Hong and Yogo (2012), I smooth these monthly growth rate series by taking a 12-month geometric average within each time series which are then referred to commodity market open interest or commodity market volume.

Panel B of Table II reports summary statistics for these additional commodity specific predictor variables. Note that the sample period for these variables is restricted to January 1986 to August 2015 because of the CFTC data availability. The average 12-month volatility of daily commodity futures returns is about 25 % and the average spot price change is 60 basis points which is twice as high as the average futures returns with higher maturity. The average hedging pressure is significantly positive which implies that on average hedgers in the commodity market are net short. Further, total open interest and trading volume in the aggregate commodity futures market is growing, since the average 12-month growth rate of open interest is 0.7 % and the average 12-month growth rate of trading volume is 1.52 %.

B.3. Macroeconomic variables

The last group contains different economic fundamentals, namely OECD aggregate industrial production (IP), total exports (EXP) and imports (IMP), the composite leading indicator (CLI) and the business confidence index (BCI). For all 5 variables, I calculate monthly growth rates and corresponding summary statistics are reported in Panel C of Table II. The monthly growth rate of industrial production has a mean of 0.17 % implying that total OECD output is slowly growing over time. Total exports and imports are growing as well with an average growth rate of 0.56 % and 0.65 %, respectively. In contrast, the average monthly changes of the composite leading indicator as well as the business confidence index is basically zero. The latter observation is expected because the indicators are detrended.

IV. Empirical Results

The first part of the empirical analysis addresses the question whether returns of an aggregate commodity portfolio are predictable. The focus is on testing the predictive power of three different measures derived from the commodity yield curve, namely the basis, the forward rates and the PC-factors extracted from the basis. The second part examines the relation between aggregate commodity returns and economic fundamentals. I investigate how commodity returns as well as the commodity yield curve vary with economic activity.

A. Predicting aggregate commodity returns

A.1. Basis regressions

The first variable to predict returns of a portfolio of commodity futures is an aggregate version of the commodity basis. Following Fama and French (1987), the basis regression model is

$$rx_{t+h}^{(n)} = \alpha^{(n)} + \beta^{(n)} basis_t^{(n)} + \varepsilon_{t+h}^{(n)} \tag{4}$$

where $n = 1, 2, 3, 4$ months to maturity, which should be the same for returns and the basis per regression and the forecasting horizon is $h = 1, 3, 6, 9, 12$ months. This model tests whether the basis at time t can predict returns h-month ahead, with a null hypothesis of $H_0 : \beta^{(n)} = 0$ against the alternative hypothesis of $H_1 : \beta^{(n)} \neq 0$. A rejection of the null hypothesis suggests that expected commodity returns are time-varying. The results are shown in Panel 1 of Table III.[7] Consistent with evidence in the literature, I find that the basis negatively predicts commodity returns, both across maturities and across horizons. Given a contangoed market (positive basis)

[7] All empirical regression results are reported for forecasting horizons of $h = 1$ and 12 months. Results for other holding periods are available on request.

the futures price is thus expected to fall, or alternatively, if the futures market is in backwardation (negative basis) expected returns are positive, which is in line with the expected behaviour of the roll yield. However, the statistical evidence for the predictive power of the commodity basis on the aggregate level is very weak. The only slope coefficient which is significant at the 10 % level is found for the 2-month maturity and 1-month forecasting horizon.[8]

A.2. Forward Factor regressions

Instead of using the basis, which corresponds to one specific point on the futures curve, I use more yield curve information to improve return forecasts. Similar to the approach developed by Cochrane and Piazzesi (2005) to predict bond excess returns, I construct a forward rates factor in a two step regression analysis. First, the average h-month commodity return across all four maturities is regressed on all four forward rates and a constant

$$\frac{1}{4}\sum_{n=1}^{4} rx_{t+h}^{(n)} = \gamma_0 + \gamma_1 f_t^{(1)} + \gamma_2 f_t^{(2)} + \gamma_3 f_t^{(3)} + \gamma_4 f_t^{(4)} + \varepsilon_{t+h} \tag{5}$$

where $f_t^{(n)} = forward_t^{(n)}$. The forward rates factor is then defined as

$$\hat{\gamma}'\mathbf{f_t} = (\hat{\gamma}_0\ \hat{\gamma}_1\ \hat{\gamma}_2\ \hat{\gamma}_3\ \hat{\gamma}_4)' \cdot (1\, f_t^{(1)}\ f_t^{(2)}\ f_t^{(3)}\ f_t^{(4)}) \tag{6}$$

which is equal to the fitted average return from the first step regression model. Second, this forward rates factor is used to predict h-month returns for each maturity

$$rx_{t+h}^{(n)} = \beta^{(n)} \cdot (\, \hat{\gamma}'\, \mathbf{f_t}\,) \tag{7}$$

where $n = 1, 2, 3, 4$ months to maturity and the forecasting horizon is $h = 1, 3, 6, 9, 12$ months. The results of the forward factor regressions given by equation (7) are reported in Panel 2 of Table III. The predictability coefficients are all highly significant across maturities and horizons. Moreover the explanatory power is at least twice the adjusted R^2s found in the basis regressions, i.e. around 1.5 %. The forward rates factor positively predicts future commodity returns and expected returns nearly move in unity with this factor. Hence, expected commodity returns are

[8]Note that existing studies, such as Fama and French (1987) or Gorton, Hayashi, and Rouwenhorst (2012), find that the statistical evidence for the basis to predict returns on commodity futures strongly depends on the type of commodity. Hence, aggregating across all different commodities seems to weaken the empirical predictability evidence of the basis.

indeed predictable when considering information along the whole futures curve instead of just one specific tenor point. Importantly this forward rates factor is the same for all regressions, meaning that a single linear combination of forward rates forecasts aggregate commodity returns at all maturities.

Cochrane and Piazzesi (2005) find that their bond return forecasting factor is a symmetric, tent-shaped linear combination of forward interest rates. To test whether this tent-shape can be observed in the regression coefficients, I run the following unrestricted regressions

$$rx_{t+h}^{(n)} = \gamma_0 + \gamma_1 f_t^{(1)} + \gamma_2 f_t^{(2)} + \gamma_3 f_t^{(3)} + \gamma_4 f_t^{(4)} + \varepsilon_{t+h} \tag{8}$$

The regression is run for each maturity $n = 1, 2, 3, 4$ months and the results are reported in Table IV. Further, this table also reports the results of the restricted regressions (step 1 and 2) which are given by equations (5) and (7), respectively. The unrestricted regression results show that aggregate commodity returns are positively driven by the 3-month forward rate and negatively by all others. Although the explanatory power increases up to 0.79 % for monthly returns, the only significant coefficient is the one for the 4-month forward rate. Similar observations hold true for the restricted step 1 regression, where the coefficients represent the loadings of the forward rate factor. Apparently, this factor is driven by the long maturity forward rate.

Figure 4 plots the γ coefficients (excluding the intercept) of all unrestricted regressions against the maturity of the corresponding forward rate. These coefficients are clearly tent-shaped being positive at 3-month maturity and negative for all others. Moreover, this pattern is consistent across all maturities which rationalizes that a single linear combination of forward rates can predict commodity returns at all maturities. Thus, similar to bond excess returns, there also exists a single return forecasting factor for aggregate commodity returns.

[Figure 4 about here.]

A.3. PC-Factor regressions

An alternative approach to incorporate more information from the futures yield curve than just the basis is to include the first three PC factors derived from the basis of different maturities which are characterized as level, slope and curvature factor and described in Section III B.1. The regression equation using all three factors jointly is given by

$$rx_{t+h}^{(n)} = \alpha^{(n)} + \beta_1^{(n)} PC_{1,t} + \beta_2^{(n)} PC_{2,t} + \beta_3^{(n)} PC_{3,t} + \varepsilon_{t+h}^{(n)} \tag{9}$$

where $n = 1, 2, 3, 4$ months to maturity and the forecasting horizon is $h = 1, 3, 6, 9, 12$ months. The results are summarized in Panel 3 of Table III. The curvature factor (PC_3) positively predicts future commodity returns across all maturities and the coefficients are statistically significant at the 5 % level, while the coefficients of the slope and level factors are not significant. Moreover, the adjusted R^2s are slightly lower compared to the predictability regressions using the forward rate factor, but remarkably higher than the explanatory power of the basis regressions.

To sum up the results so far, aggregate commodity returns are predictable and expected commodity returns are time-varying. The forward rate factor and the PC-factors use information along the whole futures curve which significantly improves overall predictability of aggregate commodity returns, compared to just using one specific point on the yield curve, i.e. the basis, to predict next period returns. Similar to the evidence found in the literature on bond returns, a single factor constructed from forward rates as well as a level, slope and curvature factor of the yield curve predict aggregate commodity returns and constitute a significant improvement over the classical forward-spot spread, i.e. the basis.

B. Relation to economic fundamentals

To understand potential economic mechanisms governing these return predictability results, I investigate how these aggregate commodity returns and the commodity yield curve vary with economic activity. In particular, the focus is on identifying whether expected commodity returns are pro- or countercyclical. To assess the business cycle properties of commodity returns and their forecasting factors, I use monthly growth rates of the five macroeconomic variables described in section III B.3.

B.1. Contemporaneous correlations

Table V reports contemporaneous correlations of commodity returns, the basis, the forward rate factor, the PC-factors, and the five macroeconomic fundamentals. The basis is negatively correlated with industrial production, export and import growth. On the other hand, the forward rate factor and the curvature factor (PC_3) are both positively correlated with all five economic fundamentals. The idea is that forecasted commodity returns should inherit the cyclical behaviour of their forecasting factors. For example, the basis negatively predicts aggregate commodity returns and it is negatively correlated with economic fundamentals, which would suggest a procyclical behaviour of expected commodity returns. In times of economic growth, the commodity basis will be low or even negative (backwardation) and thus predict positive returns on commodity futures. The intuition is easier when looking at the other two dominant return forecasting factors. The forward rate as well as the curvature factor positively predict aggregate commodity returns and are positively correlated with economic fundamentals, hence, expected returns should be procyclical. Nevertheless, these contemporaneous correlations and the subsequent deductions are just a first indication that expected returns on an aggregate commodity portfolio might be procyclical.

B.2. Augmented baseline regressions

To test this observation more formally, I augment the baseline regression models given in Section IV. A by including one economic fundamental as additional predictor variable at a time.[9] Similar to Lustig, Roussanov, and Verdelhan (2014), I run the following regression model

$$rx_{t+h}^{(n)} = \alpha^{(n)} + \beta^{(n)} F_t + \gamma^{(n)} X_t + \varepsilon_{t+h}^{(n)} \tag{10}$$

where $n = 1, 2, 3, 4$ months to maturity and the forecasting horizon is $h = 1, 3, 6, 9, 12$ months. F_t represents the forecasting factor which is either the basis, the forward rate factor or all three PC-factors and X_t represents the economic fundamental, i.e. $F_t \in \{basis_t^{(n)}, \hat{\gamma}' \mathbf{f_t}, [PC_{1,t}, PC_{2,t}, PC_{3,t}]\}$ and $X_t \in \{IP_t, CLI_t, BCI_t, EXP_t, IMP_t\}$. Hence, h-month commodity returns are regressed on a constant, one baseline predictor and one economic fundamental. Under the null hypothesis, $H_0 : \gamma^{(n)} = 0$, expected commodity returns do not vary with the growth rate of economic activity and today's output growth is irrelevant for next period's commodity prices. Conversely, the alternative hypothesis posits that $H_1 : \gamma^{(n)} \neq 0$ and expected commodity prices do react to current economic conditions. If $\gamma^{(n)} > 0$, expected commodity returns are said to by procyclical since high economic growth at time t will influence aggregate commodity prices and lead to

[9]Baseline models refer to regressions (4), (7) and (9).

positive expected returns h-month ahead. Alternatively, $\gamma^{(n)} < 0$ suggests that expected returns of an aggregate commodity portfolio are countercyclical.

Table VI summarizes the results of these macroeconomic predictability regressions. The columns labelled "Model" refer to one of the three baseline factors and the rows specify the corresponding economic fundamental. For each combination of forecasting factors, the table reports results for maturities, n, of 1 and 4 months, as well as a forecasting horizon, h, of 1 (Panel A) and 12 months (Panel B).[10] First, economic fundamentals positively predict aggregate commodity returns. Their predictive power holds across maturities and it is strongest for short forecasting horizons, i.e. at a monthly horizon all $\gamma^{(n)}$ coefficients are highly significant at a 5 % level. On average the explanatory power given by the adjusted R^2 slightly increases with the remaining time to maturity, n, implying that prices of commodity futures with longer time to maturity are more sensitive to current economic conditions. Second, using the forward rate factor or the PC-factors jointly with economic fundamentals raises overall predictability as measured by the R^2_{adj} to 7 %. In terms of baseline factors, the weakest one is the basis which is never significant and hardly adds any predictive power while the forward rate factor is the most dominant baseline predictor and its marginal significance is not reduced compared to the baseline model. Regarding the economic fundamentals, the monthly changes of the composite leading indicator as well as the business confidence index have the strongest predictive power and their coefficients are significant across all different specifications.

Economically, these results imply that expected aggregate commodity returns are positive, when industrial production or global trade increases. For example, a 1 % increase in total OECD industrial production predicts positive returns of over 70 basis points for the next month for an aggregate commodity portfolio. Note that these returns are already in excess of the risk-free rate and without leverage, since futures positions are fully collateralized. Similarly, a monthly growth rate of 1 % in global exports or imports of goods and services corresponds to expected monthly commodity returns of nearly 15 basis points. Further, commodity prices are expected to increase when managers are more confident about future business developments or when different economic variables, aggregated to a composite leading indicator, point at higher economic activity.

From these findings I conclude that expected returns of an aggregate commodity portfolio are procyclical. In economic terms, this means that an increase in global economic activity raises

[10]Further results are available on request.

the demand for commodities as production inputs. Consequently, a higher commodity demand pushes up commodity spot prices and reduces existing inventories since commodity supply is rather inelastic and it is difficult to adjust production immediately. Moreover, higher economic activity raises commodity spot prices more than futures prices due to the fact that production inputs are needed immediately and not n months in the future. Hence, the commodity yield curve gets inverted (backwardation) and expected returns are high. Conversely, in times of economic downturn the demand for commodities as production inputs decreases which in turn leads to a fall in spot prices and a rise in inventory levels. This decrease in commodity demand, due to a decline in industrial production, affects spot prices more strongly than futures prices which results in an upward sloping commodity yield curve (contango). Hence, aggregate commodity returns are expected to be low. Overall, these results show that expected returns on commodity futures move in sync with economic activity and can thus be classified as procyclical.

C. Out-of-sample return predictability

Previous results and observations rely on in-sample return predictability analysis. They document that commodity returns are predictable and some promising predictor variables have been identified, such as the forward rate factor or different economic fundamentals. However, to further use these results for investment purposes, one needs a proper out-of-sample backtest of these models and variables. That is, I use the first 10 years of data, i.e. January 1975 to December 1984, to calibrate the model and estimate the regression parameters. Using these coefficient estimates together with the December 1984 observation of the predictor variables, I obtain the first out-of-sample return forecast for January 1985 (forecasting horizon of 1 month). After one month, I re-estimate the model with extended data from January 1975 to January 1985, to predict the out-of-sample return for the next month. This iterative procedure is repeated every month over an expanding data window to get consistent out-of-sample forecasts that are free from any forward-looking bias. Hence, out-of-sample forecasts can be evaluated from January 1985 to August 2015.

In order to investigate the reliability of the baseline predictors as well as the economic fundamentals for possible investment purposes, I estimate out-of-sample commodity return forecasts using regression equation (10) for $n = 1, 2, 3, 4$ months to maturity and a forecasting horizon of

$h = 1, 3, 6, 9, 12$ months. Note that the forward rate factor and the PC-factors are re-estimated each month to avoid any in-sample overfitting. To evaluate these out-of-sample return forecasts I use the Campbell and Thompson (2008) R^2_{OOS} statistic, which compares the forecast accuracy of a given predictive (regression) model relative to the historical average return forecast. In particular, a positive R^2_{OOS} indicates that the model-based return forecast has a lower mean squared forecast error than the historical average forecast, i.e. it is more accurate, and vice-versa if the R^2_{OOS} is negative. To test whether the model based return forecasting improvement is also statistically significant, I rely on the Clark and West (2007) MSFE-adjusted test statistic.[11]

Table VII reports R^2_{OOS} together with the MSFE-adjusted statistic for the macroeconomic predictability regression forecasts. The columns labelled "Model" again refer to the baseline factor and the rows indicate the economic fundamental used. The results are shown for maturities 1 and 4 months and a forecasting horizon of 1 month. First, the basis together with any economic fundamental can significantly predict commodity returns out-of-sample, i.e. all R^2_{OOS} are positive and significant. Second, the out-of-sample performance of the forward rate or PC-factors is somewhat weaker than in-sample. In terms of economic fundamentals, only aggregate indices such as the CLI or BCI can produce consistent out-of-sample commodity return forecasts. Hence, these results indicate that the superior in-sample ability of the forward rate or PC-factors to predict aggregate commodity returns is partly due to overfitting. Indeed, these factors are constructed using the whole data sample, and only then used as return predictors. Still, in line with Cochrane and Piazzesi (2005) and others, these factors are valid to establish return predictability in the first place. Nevertheless, these out-of-sample results highlight the importance of the basis as a reliable commodity return predictor, even on the aggregate portfolio level and even if in-sample performance is rather weak. Furthermore, current economic activity is indeed an important indicator for future expected commodity returns, both in- and out-of-sample.

Following Goyal and Welch (2003, 2008) and Rapach and Zhou (2013) I compute the cumulative difference in squared forecast errors (CDSFE) to evaluate the model-based out-of-sample commodity return forecasts relative to the historical average forecast, both graphically and over time. Figure 5 plots the CDSFE based on regression model (10) using monthly growth rates of industrial production as well as the composite leading indicator together with each of the three

[11] Formally, the MSFE-adjusted statistic tests the null hypothesis, $H_0 : R^2_{OOS} \leq 0$, against the alternative hypothesis, $H_1 : R^2_{OOS} > 0$.

baseline predictors. Out-of-sample commodity return forecasts are calculated for a maturity and forecasting horizon of 1 month. If the CDSFE curve has a positive slope over any time period, the regression model forecast has a lower MSFE than the historical average during that period, and vice versa.

The most striking out-performance across all plotted model specifications against the historical average benchmark is obtained during the recent financial crisis around 2009. This superior out-of-sample forecast accuracy is even more pronounced when using the composite leading indicator as economic fundamental instead of the industrial production growth rate, independent of the baseline predictor. Nevertheless, when comparing the out-of-sample forecasting performance of the baseline factors, one observes that the forward rate factor produces the least accurate forecasts, i.e. the FW-factor CDSFE curve is always lower than the corresponding basis or PC-factors CDSFE curves. Hence, in-sample superiority does not translate into out-of-sample consistency. Moreover, Figure 5 also highlights the out-of-sample forecasting strength of the basis. In particular, starting around 2001 the CDSFE curves corresponding to regression models using the basis rise relatively more than the forward rate or PC-factors CDSFE curves. Overall, aggregate commodity returns are predictable and combining commodity yield curve factors together with different economic fundamentals gives risk to meaningful out-of-sample return forecasts, particularly during economic downturns.

[Figure 5 about here.]

V. Robustness Analysis

The following section investigates whether the results found in the previous analysis are robust to different regression specifications and tests how they relate to other findings in the literature. For example, do the new baseline factors, such as the forward rate or PC-factors, remain significant when additional predictor variables are included in the regression model or is their predictive power subsumed by other variables known to predict commodity returns. Second, is the predictive dominance of the economic fundamentals due to a publication lag in macroeconomic time-series and hence, significance is due to a look-ahead bias? Further, this section addresses the question whether commodity return predictability is different during expansions or recessions to get a better understanding of the cyclicality of expected commodity returns. Last and most relevant for investors is the analysis on predicting commodity index returns.

A. Additional predictor variables

Similar to Hong and Yogo (2012) I test the marginal significance of the baseline variables in a multiple predictive regression framework, where I include other commodity yield factors which are partly suggested by theory or found in the literature to predict commodity returns. These variables include hedging pressure (hp_t), commodity market open interest (oi_t) and changes in trading volume ($volume_t$) as well as spot returns ($spot_t$) and the volatility of returns ($vola_t$). Hence, the extended regression model is

$$rx_{t+h}^{(n)} = \alpha^{(n)} + \beta_1^{(n)} F_t + \beta_2^{(n)} vola_t + \beta_3^{(n)} spot_t + \beta_4^{(n)} hp_t + \beta_5^{(n)} oi_t + \beta_6^{(n)} volume_t + \varepsilon_{t+h}^{(n)} \quad (11)$$

where $n = 1, 2, 3, 4$ months to maturity and the forecasting horizon is $h = 1, 3, 6, 9, 12$ months. F_t again represents the forecasting factor which is either the basis, the forward rate factor or all three PC-factors, i.e. $F_t \in \{basis_t^{(n)}, \hat{\gamma}' \mathbf{f_t}, [PC_{1,t}, PC_{2,t}, PC_{3,t}]\}$. Note that the forward rate and PC-factors are first estimated independently from the additional predictor variables and included in the multiple regression model afterwards. Due to data availability, these regressions are estimated for the sample period ranging from January 1986 to August 2015.

The results are summarized in Table VIII, which is arranged in three Panels corresponding to the baseline factors. At a monthly forecasting horizon (columns 3 to 5), the growth rate of open interest dominates all other predictor variables and it significantly predicts aggregate commodity returns across all maturities and independent of the baseline factor. However, price related measures such as spot returns or past volatility of returns significantly improve overall predictability at longer horizons, i.e. at an annual forecasting horizon (columns 6 to 8). It seems that the dominant predictive power of the baseline factors is partly subsumed by open interest growth at a monthly horizons: only the forward rate factor at longer maturities and the curvature factor (PC_3) are marginally significant. Hence, these results are consistent with the conclusions drawn by Hong and Yogo (2012) who posit that open interest contains information about future commodity supply and demand, which is not captured by futures prices in the short run. According to them, asset prices initially underreact to news about economic activity and inflation expectations, which is better captured by open interest, since prices adjust only after a few months. Furthermore, the hedging pressure is never significant neither at the monthly or annual horizon nor at short or long maturities. Although the coefficients are positive (which is in line with the theory of normal backwardation, i.e. net short positions by hedgers imply positive expected returns on commodity futures), their predictive power is obviously subsumed by more dominant variables. Thus, the theory of normal backwardation is less relevant for describing expected returns, at least on the aggregate commodity market level. Nevertheless, the explanatory power of the extended regression model is more than doubled with adjusted R^2s of over 3 %, compared to the baseline regression models.

B. Lagged predictor variables

To account for possible publication lags in macroeconomic time-series which might result in some look-ahead bias, I adjust the macroeconomic predictability regression model by lagging the economic fundamental variable even further. The adapted regression model is

$$rx_{t+h}^{(n)} = \alpha^{(n)} + \beta^{(n)} F_t + \gamma^{(n)} X_{t-l} + \varepsilon_{t+h}^{(n)} \tag{12}$$

where $n = 1, 2, 3, 4$ months to maturity, the forecasting horizon is $h = 1, 3, 6, 9, 12$ months and the publication lag is $l = 1, 3, 6, 9, 12$ months. Hence, the current value of the baseline factor, F_t, and the growth rate of the economic fundamental l-month ago, X_{t-l}, are used to predict aggregate commodity returns h-month ahead.

Table IX summarizes the results for a lag of 1 month (Panel A) and 3 months (Panel B), where the forecasting horizon is always 1 month.[12] First, at a publication lag of 1 month all economic fundamentals except exports and imports are still significant predictors for future commodity returns, across maturities and independent of the baseline factor. Second, at a lag of 3 months only monthly changes of the OECD composite leading indicator can significantly predict aggregate commodity returns. The coefficients of all other variables turn insignificant. Comparing Panel A of Table IX with Panel A of Table VI, one can observe that lagging economic fundamentals reduces the magnitude of the $\gamma^{(n)}$ coefficients as well as the adjusted R^2s. Hence, the current growth rate of different economic variables contains the most information about future commodity

[12] Further results for different lags, horizons and maturities are available on request.

prices. However, even with a publication lag of one month most results in terms of statistical significance continue to hold, albeit with smaller economic magnitude. Moreover, the regression coefficients of lagged economic fundamentals are all positive, implying that expected aggregate commodity returns are procyclical.

C. Predictability during expansions and recessions

Gargano and Timmermann (2014) find evidence that commodity spot return predictability is mostly a recessionary phenomenon and largely absent during economic expansions.[13] First, I investigate whether a similar pattern is present when predicting aggregate commodity futures returns. Second, the following analysis should help further rationalizing business cycle properties of expected commodity returns. Therefore, I estimate the baseline regression models separately for U.S. expansions and recessions where I use the NBER business cycle indicator as a classification dummy.[14] The state-dependent regression model is specified as follows

$$rx_{t+h}^{(n)} = \alpha_{EXP}^{(n)} + \alpha_{REC}^{(n)} I_t + \beta_{EXP}^{(n)} F_t + \beta_{REC}^{(n)} F_t I_t + \varepsilon_{t+h}^{(n)} \tag{13}$$

where $n = 1, 2, 3, 4$ months to maturity and the forecasting horizon is $h = 1, 3, 6, 9, 12$ months. I_t represents the business cycle indicator, which is 1 in times of an NBER recession and 0 during expansion periods. F_t again refers to one of the three baseline factors. Note that the parameters $\alpha_{REC}^{(n)}$ and $\beta_{REC}^{(n)}$ just measure marginal effects. In order to get the total recession effect, one has to add the corresponding coefficients, i.e. $\alpha_{EXP}^{(n)} + \alpha_{REC}^{(n)}$ and $\beta_{EXP}^{(n)} + \beta_{REC}^{(n)}$.

Table X presents the results where each Panel, labelled "Model", refers to one of the three baseline factors. First, the forward rate and curvature factor (PC_3) significantly predict aggregate commodity returns during NBER expansions with a positive coefficient, across maturities and horizons. Second, the coefficients during recessions are negative implying lower expected returns than in expansions, however they are only significant at longer horizons. Economically,

[13]Similarly, Henkel, Martin, and Nardari (2011) and Rapach, Strauss, and Zhou (2010) document that the predictability of stock returns is strongest during recessions.

[14]The NBER recession indicator is an ex-post measure of the economic state and hence, only suitable for in-sample analysis. Moreover, during the sample period of January 1975 to August 2015, only 58 out of 488 months are classified as recessions, which implies a very small sample size hampering a proper statistical inference of the estimated recession parameters. Despite these challenges, the objective of the following analysis is to relate the empirical findings to the literature on stock return predictability. Furthermore, it allows to investigate the in-sample business cycle behaviour of aggregate commodity returns.

these results indicate that aggregate commodity returns are expected to be positive and high during economic expansions, whereas they tend to be low or partly even negative during recessions. Hence, expected commodity returns are clearly procyclical, increasing with economic activity and decreasing during downturns, which is consistent with the evidence found when using different economic fundamentals to predict returns. Third, it seems that aggregate commodity return predictability is an expansionary phenomenon which is clearly in contrast to the findings on stock return predictability. Of course the weak statistical significance of estimated recession coefficients is partly due to the small sample size, however studies on the state-dependencies of stock returns are prone to the same problem. Still, the results are different and I find that the predictability of commodity returns is strongest during expansions and their business cycle behaviour is procyclical. Furthermore, the adjusted R^2s of these state-dependent regressions are significantly higher than the ones of the baseline regressions. Hence, the explanatory power of the baseline factors seems to increase if we account for the economic state when predicting aggregate commodity returns. Last, the coefficients of the basis are insignificant across all maturities and horizons, implying that the basis cannot predict aggregate commodity returns even if we account for state-dependencies. Thus, using information along the whole futures curve significantly improves the in-sample predictive power and allows to analyze state-dependencies and the business cycle behaviour of expected commodity returns.

D. Predicting commodity index returns

To test the relevance of these identified commodity return predictors for investors, I use the baseline factors together with the economic fundamentals to predict returns on commodity indices. That is, I estimate the macroeconomic predictability regression model given by equation (10), but instead of forecasting returns on a constructed commodity portfolio I use monthly returns on the SP-GSCI as well as the DJ-UBS commodity index. Note that these indices are not available for different maturities, since they are always rolled over to the nearest contract.

Panel A of Table XI presents the results for predicting monthly SP-GSCI returns. First, the aggregate commodity basis significantly predicts SP-GSCI returns. The coefficients are negative which is in line with the expected roll yield, i.e. positive returns in a backwardated futures market and negative returns when the commodity market is in contango. Interestingly, the aggregate basis can predict expected returns on a commodity index but not on its own commodity portfolio. Second, the coefficients of the forward rate and curvature (PC_3) factor are all highly significant, positive and their magnitude is remarkably higher than the corresponding coefficients when predicting aggregate commodity returns (see Panel A of Table VI). This implies that the information along the aggregate futures curves seems to be very relevant for commodity index returns. Third, all economic fundamentals, except export growth, significantly predict monthly returns on the SP-GSCI and their marginal effect is stronger than for aggregate commodity returns (i.e. the γ coefficients in Table XI are twice the size of the $\gamma^{(n)}$ coefficients in Table VI). Moreover, all coefficients are positive implying that commodity index returns are also procyclical and increase with economic activity. Overall, the explanatory power, i.e. adjusted R^2s, of these macroeconomic predictability regressions is very similar when predicting aggregate commodity returns or commodity index returns.

Panel B of Table XI reports results for predicting monthly returns on the DJ-UBS commodity index. Due to data availability the sample period is shorter and starts in January 1991 to August 2015. Although the marginal effects of all baseline factors are insignificant, all economic fundamentals, expect export growth, are highly relevant for predicting returns on this index. Similarly, their coefficients are positive and DJ-UBS commodity index returns are also procyclical. To sum up, the macroeconomic predictive regression model also allows to forecast monthly returns of tradable commodity indices.

VI. Sector Analysis

This section addresses the question whether the results found for aggregate commodity returns also hold at the commodity sector level. That is, can the baseline factors as well as economic fundamentals also predict different commodity sector returns? The five sectors which are analyzed are Energy, Grains and Oilseeds, Livestock, Metals and Softs. A detailed list of individual commodities in each sector is found in Table I. The sample period for the sectors Grains, Livestock and Softs is January 1975 to August 2015, whereas the sectors Energy and Metals only start in January 1986 to August 2015. The aggregation of variables on the sector level (i.e. returns, basis and forward rates) is described in section III.

A. Predicting commodity sector returns

First, I estimate the three baseline regressions specified by equations (4), (7) and (9) for each sector. Note that the forward rate factor as well as the principal component analysis is also reestimated for each sector. The results are summarized in Table XII.

The empirical evidence of the basis to predict commodity returns is also very weak at the sector level. At the monthly horizon, the basis can only forecast long maturity returns of Grains and Metals. Moreover, the coefficients for Grains and Softs are even positive, which is contrary to the expected roll yield, however they are statistically insignificant. At an annual horizon, the basis negatively predicts returns of Livestock and Metals, with 5 % significance. In contrast to the basis, the forward rate factor significantly predicts sector commodity returns across all maturities and horizons. Hence, using information along the whole futures curve also works at the sector level and significantly improves in-sample return predictability. The results for Model 3 show that the empirical performance of the first three principal components derived from the basis to predict commodity returns is less consistent at the sector level than it was for the aggregate commodity portfolio. Only the first and second PC-factor significantly predict Metal returns, and the dominance of the curvature (PC_3) factor has vanished. Overall, I find that commodity sector returns are predictable in-sample. While the empirical evidence of the basis is very weak, the results show that using information along the whole futures curve significantly improves predictability across all sectors. Further, there are no significant differences across the five sectors.

B. Relation to economic fundamentals

Second, I estimate the macroeconomic predictability regression model given by equation (10) for each sector to investigate the cyclical properties of commodity sector returns. Table XIII summarizes the results for a forecasting horizon of 1 month and a maturity of 1 month. Across all five sectors and independent of the baseline factor, economic fundamentals positively predict monthly commodity sector returns. Hence, expected commodity sector returns are also procyclical – increasing with economic activity and decreasing during downturns. Of course the marginal effects vary across sectors, implying that some commodities are more sensitive to current economic conditions. Regarding the predictive power of individual economic fundamentals, the results show that monthly changes in the OECD composite leading indicator as well as the business confidence index can significantly predict next month commodity returns of all sectors. While expected returns of Energy and Metals are very sensitive to aggregate economic conditions, with CLI or BCI coefficients of around 10, the corresponding coefficients of Grains and Softs are only around 5 and Livestock returns are the least sensitive with coefficients of only 2. Further, monthly growth rates of global industrial production significantly predict commodity returns of the sectors Energy, Metals and Softs, while growth rates of world exports and imports can predict returns of Energy and Softs only. On the other hand, commodity returns of the sectors Grains and Livestock are less affected by economic conditions.

These cross-sectional differences in sensitivities to economic conditions across commodity sectors are consistent with the economic explanation for the cyclical properties of commodity returns. That is, higher economic activity increases the demand for commodities as production inputs, which in turn raises the spot price and reduces existing inventories. As a result, the commodity yield curve gets inverted (backwardation) and expected returns on commodity futures are high and positive. For this mechanism to work, the effect on commodity demand and the consequent reaction of commodity spot prices and inventories is essential. I posit that this effect is much stronger for commodities serving as production inputs for different industries. This is certainly the case for Energy and Metals and to a certain degree also for Softs (which contains for example Ethanol, Cotton or Sugar). On the other hand Grains and Oilseeds as well as Livestock are not used as inputs for industrial production and hence the demand for these commodities is rather inelastic to changes in production. Moreover, the demand for raw materials needed for food production, which are basically Grains and Livestock, does not vary with economic activity or the business cycle. Thus, these differences in commodity demand caused by time-variation in industrial production translate to different marginal effects of economic fundamentals in the predictability of commodity sector returns. While returns of Energy, Metals and Softs are very sensitive to economic conditions with highly significant γ coefficients, returns of Grains and Livestock do not react to changes in economic activity.

Third, I estimate out-of-sample forecasts for commodity sector returns using again regression equation (10). I use the first 10 years of data as an initial in-sample estimate, which is for the sectors Grains, Livestock and Softs January 1975 to December 1984 and for Energy and Metals it is January 1986 to December 1995. Then, out-of-sample forecasts are evaluated using an expanding data window until August 2015 and an iterative estimation procedure which is outlined in section IV. C. Table XIV summarizes the results for a forecasting horizon of 1 month. It shows the R^2_{OOS} together with the MSFE-adjusted statistic for each macroeconomic predictive regression forecast. Similar to the out-of-sample forecast of aggregate commodity returns, the best forecasting performance is achieved by using the basis as baseline factor together with monthly changes of the OECD composite leading indicator or business confidence index. Regarding the performance across sectors, the macroeconomic predictive regression model performs best also out-of-sample for Energy, Metal and Softs returns since they are most sensitive to economic conditions. On the other hand, the out-of-sample forecasts of Grains and Livestock returns are statistically very weak.

To sum up, commodity sector returns are predictable. In-sample, the forward rate factor dominates the basis and principal component factors derived from the basis. Hence, using information along the whole futures curve significantly improves in-sample predictability. However, out-of-sample the basis achieves the best out-of-sample forecasting performance compared to the other baseline factors. Moreover, returns on commodities which are demanded as production inputs are very sensitive to economic activity, whereas other commodities which are rather used for food than industrial production are less affected by current economic conditions. These characteristics translate to significant marginal effects when using economic fundamentals to predict future commodity sector returns. Overall, expected returns on commodity sector portfolios are procyclical.

VII. Conclusion

Using data on futures prices of 32 different commodities across 5 sectors over the period from 1975 to 2015, I find evidence that commodity returns are predictable both on an aggregate portfolio as well as at the sector level. In contrast to some theoretical result, the basis is a very poor predictor of aggregate commodity returns. Instead, I construct a factor using different forward rates along the futures curve and find that aggregate and sector commodity returns are predictable. Similarly, the third principal component factor derived from the basis, which is related to the curvature of the futures curve, is highly relevant for commodity return predictability. While these factors derived from the whole futures curve significantly improve in-sample predictability, the basis achieves the best out-of-sample forecasting performance.

Second, I find evidence that expected aggregate commodity returns are procyclical and that the time-variation in the commodity yield curve is strongly linked to the business cycle. Economic fundamentals, such as industrial production or global trade, positively predict aggregate and sector commodity returns. Using economic fundamentals jointly with these yield curve factors significantly raises overall predictability in- and out-of-sample. I argue that higher economic activity increases the demand for commodities as input factors, which in turn raises commodity spot prices and lowers inventories. As a result, the commodity yield curve gets inverted (backwardation) and expected returns on commodity futures are high. Results on sector return predictability show that commodities which are demanded as production inputs, such as Energy and Metals, are very sensitive to changes in economic activity, whereas other commodities which are rather used for food than industrial production are less affected by current economic conditions. These characteristics translate to cross-sectional differences in marginal effects when using economic fundamentals to predict future commodity sector returns.

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Table I
Commodity Futures Data

The table lists all 32 commodities grouped by sector together with the exchange on which they are traded, the corresponding Bloomberg ticker symbol, the year of the first recorded observation, the delivery months used and the corresponding code in the Commitment of Traders reports issued by the Commodity Futures Trading Commission (CFTC). The commodity futures contracts are traded on the Chicago Board of Trade (CBOT), the Chicago Mercantile Exchange (CME), the New York Commodities Exchange (COMEX), the Intercontinental Exchange (ICE), the London Metal Exchnage (LME) and the New York Mercantile Exchange (NYMEX).

Sector	Commodity	Exchange	Ticker	Year	Delivery Months	CFTC Code
Energy	Brent Crude Oil	ICE	CO	1990	1 : 12	ICE website[1]
	Gasoil	ICE	QS	1989	1 : 12	ICE website
	Gasoline	NYMEX	HU/XB	1988	1 : 12	111659
	Heating Oil	NYMEX	HO	1987	1 : 12	022651
	Natural Gas	NYMEX	NG	1991	1 : 12	023651
	WTI Crude Oil	NYMEX	CL	1984	1 : 12	067651
Grains & Oilseeds	Corn	CBOT	C	1960	3, 5, 7, 9, 12	002601, 002602
	Rough Rice	CBOT	RR	1990	1, 3, 5, 7, 9, 11	039601, 039781
	Soybean Meal	CBOT	SM	1960	1, 3, 5, 7, 8, 9, 10, 12	026603
	Soybean Oil	CBOT	BO	1960	1, 3, 5, 7, 8, 9, 10, 12	007601
	Soybeans	CBOT	S	1960	1, 3, 5, 7, 8, 9, 11	005601, 005602
	Wheat	CBOT	W	1960	3, 5, 7, 9, 12	001601, 001602
Livestock	Feeder Cattle	CME	FC	1973	1, 3, 4, 5, 8, 9, 10, 11	061641
	Lean Hogs	CME	LH	1987	2, 4, 6, 7, 8, 10, 12	054641, 054642
	Live Cattle	CME	LC	1966	2, 4, 6, 8, 10, 12	057642
Metals	Gold	COMEX	GC	1975	2, 4, 6, 8, 10, 12	088691
	Palladium	COMEX	PA	1987	3, 6, 9, 12	075651
	Platinum	COMEX	PL	1987	1, 4, 7, 10	076651
	Silver	COMEX	SI	1976	1, 3, 5, 7, 9, 12	084691
	Aluminium	LME	LA	1998	1 : 12	na
	Copper	LME	LP	1998	1 : 12	085691, 085692
	Lead	LME	LL	1998	1 : 12	na
	Nickel	LME	LN	1998	1 : 12	na
	Tin	LME	LT	1998	1 : 12	na
	Zinc	LME	LX	1998	1 : 12	na
Softs	Ethanol	CME	DL	2006	1 : 12	025601
	Lumber	CME	LB	1987	1, 3, 5, 7, 9, 11	058641, 058643
	Cocoa	ICE	CC	1960	3, 5, 7, 9, 12	073732
	Coffee	ICE	KC	1973	3, 5, 7, 9, 12	083731
	Cotton	ICE	CT	1963	3, 5, 7, 10, 12	033661
	Orange Juice	ICE	JO	1967	1, 3, 5, 7, 9, 11	040701
	Sugar	ICE	SB	1962	3, 5, 7, 10	080732

[1] The CFTC data for Brent Crude Oil and Gasoil is taken directly from the ICE website, `https://www.theice.com/marketdata/reports/122`

Table II
Summary Statistics

The table gives summary statistics for all variables grouped into commodity futures data, additional commodity specific predictors and macroeconomic fundamentals. It reports the monthly mean, standard deviation, skewness, kurtosis and first-order autocorrelation. All data are monthly series and expressed in percentage points. The time period for Panel A and C is January 1975 to August 2015, while Panel B starts in January 1986 to August 2015.

Variable	n	mean	std deviation	skewness	kurtosis	AR(1)
Panel A: commodity futures data (1975-2015)						
returns	1	0.28	3.64	−0.47	5.25	0.13
	2	0.23	3.59	−0.54	5.46	0.13
	3	0.27	3.60	−0.51	5.25	0.12
	4	0.26	3.57	−0.45	5.30	0.13
basis	1	0.22	0.57	0.35	4.16	0.23
	2	0.30	0.50	0.03	3.30	0.69
	3	0.27	0.56	0.02	3.47	0.73
	4	0.26	0.52	0.07	3.53	0.78
forward rates	1	0.22	0.57	0.35	4.16	0.23
	2	0.23	0.51	0.22	3.32	0.28
	3	0.19	0.66	0.18	4.42	0.18
	4	0.18	0.63	0.38	6.10	0.19
Panel B: additional predictors (1986-2015)						
volatility	1	25.33	4.31	1.24	6.10	0.99
spot change	0	0.60	3.40	−0.55	6.05	0.09
hedging pressure	all	10.75	5.99	−0.50	3.25	0.80
open interest	all	0.70	1.10	−0.25	4.41	0.93
volume	1	1.52	3.03	0.81	5.72	0.22
Panel C: macroeconomic variables (1975-2015)						
industrial production		0.17	0.61	−1.62	11.11	0.29
composite leading indicator		0.01	0.16	−0.27	6.80	0.96
business confidence index		0.01	0.17	−0.40	6.91	0.89
exports		0.56	2.52	−0.44	5.30	0.09
imports		0.65	3.08	0.36	10.34	−0.02

Table III
Baseline Regressions

The table presents results of three different commodity return predictability regressions given by equations (4), (7) and (9). Estimates of the constant terms are not tabulated. The sample period is January 1975 to August 2015. Point estimates are reported with Newey and West (1987) standard errors using $h-1$ lags. * and ** indicate significance at the 10 % or 5 % levels, respectively.

		h = 1 month			h = 12 months		
Variable	n	$\beta^{(n)}$	se	R^2_{adj}	$\beta^{(n)}$	se	R^2_{adj}
Model 1: Basis							
	1	−0.33	(0.32)	0.07	−2.22	(2.59)	0.40
	2	−0.69*	(0.36)	0.71	−4.24	(3.27)	1.54
	3	−0.10	(0.32)	−0.18	−2.16	(3.17)	0.33
	4	−0.17	(0.34)	−0.14	−2.56	(3.56)	0.42
Model 2: Forward Factor							
	1	1.02**	(0.30)	1.46	1.04**	(0.35)	1.38
	2	0.99**	(0.30)	1.59	0.94**	(0.35)	1.52
	3	0.99**	(0.30)	1.40	1.01**	(0.37)	1.24
	4	1.01**	(0.30)	1.54	1.01**	(0.38)	1.05
Model 3: PC-Factors							
PC_1	1	−0.17	(0.19)	1.24	−1.76	(1.84)	1.10
PC_2		0.54	(0.48)		−0.41	(2.62)	
PC_3		2.02**	(0.72)		6.05**	(2.98)	
PC_1	2	−0.19	(0.18)	1.33	−1.81	(1.77)	1.31
PC_2		0.51	(0.48)		−0.86	(2.67)	
PC_3		2.03**	(0.71)		6.15**	(2.89)	
PC_1	3	−0.16	(0.19)	0.98	−1.42	(1.85)	0.49
PC_2		0.43	(0.47)		−0.83	(2.50)	
PC_3		1.89**	(0.72)		4.80	(3.05)	
PC_1	4	−0.15	(0.18)	0.79	−1.23	(1.89)	0.19
PC_2		0.42	(0.48)		−0.93	(2.42)	
PC_3		1.75**	(0.72)		4.03	(3.17)	

Table IV
Forward Rates Regressions

The table presents results of the unrestricted forward rates regressions corresponding to equation (8). Further, it gives the results of the restricted step 1 and 2 regressions corresponding to equations (5) and (7). Estimates of the constant terms are not tabulated. The sample period is January 1975 to August 2015. Point estimates are reported with Newey and West (1987) standard errors using $h-1$ lags. * and ** indicate significance at the 10 % or 5 % levels, respectively.

		h = 1 month			h = 12 months		
Model	n	γ_i , $\beta^{(n)}$	se	R^2_{adj}	γ_i , $\beta^{(n)}$	se	R^2_{adj}
Unrestricted	1	−0.42	(0.37)	0.65	−0.92	(1.78)	0.62
		−0.20	(0.35)		−2.24	(1.89)	
		0.40	(0.31)		−0.95	(1.33)	
		−0.48*	(0.27)		−0.71	(1.30)	
	2	−0.45	(0.37)	0.79	−0.73	(1.70)	0.76
		−0.19	(0.35)		−2.27	(1.82)	
		0.42	(0.31)		−1.11	(1.33)	
		−0.49*	(0.27)		−0.79	(1.27)	
	3	−0.35	(0.37)	0.59	−0.30	(1.79)	0.42
		−0.17	(0.35)		−1.13	(1.95)	
		0.34	(0.31)		−1.27	(1.33)	
		−0.52*	(0.27)		−1.59	(1.37)	
	4	−0.35	(0.36)	0.75	−0.13	(1.85)	0.35
		−0.06	(0.36)		−0.34	(2.05)	
		0.34	(0.31)		−1.30	(1.32)	
		−0.60**	(0.26)		−2.10	(1.42)	
Restricted, Step 1	average	−0.39	(0.37)	0.70	−0.52	(1.77)	0.48
		−0.15	(0.35)		−1.49	(1.91)	
		0.38	(0.31)		−1.16	(1.32)	
		−0.52**	(0.26)		−1.30	(1.32)	
Restricted, Step 2	1	1.02**	(0.30)	1.46	1.04**	(0.35)	1.38
	2	0.99**	(0.30)	1.59	0.94**	(0.35)	1.52
	3	0.99**	(0.30)	1.40	1.01**	(0.37)	1.24
	4	1.01**	(0.30)	1.54	1.01**	(0.38)	1.05

Table V
Contemporaneous Correlations

The table gives contemporaneous correlations between aggregate commodity returns, the basis, the forward rate factor, the PC-factors and five macroeconomic fundamentals, namely industrial production growth (IP), export and import growth (EXP, IMP), monthly change of the composite leading indicator (CLI) and the change in the business confidence index (BCI). Reported returns and the basis have one month to maturity. The sample period is January 1975 to August 2015, except correlations with exports and imports start in January 1986.

	Returns	Basis	FW-Factor	PC_1	PC_2	PC_3
Returns	1.00					
Basis	−0.17	1.00				
FW-Factor	0.13	−0.41	1.00			
PC_1	−0.19	0.86	−0.50	1.00		
PC_2	−0.02	−0.47	0.00	0.01	1.00	
PC_3	−0.02	0.11	0.31	−0.02	0.00	1.00
IP	0.17	−0.06	0.06	−0.12	−0.09	0.01
CLI	0.32	0.02	0.01	0.00	−0.02	0.07
BCI	0.36	0.02	0.01	−0.02	−0.05	0.06
EXP	0.28	−0.15	0.12	−0.16	0.03	0.02
IMP	0.23	−0.12	0.14	−0.15	0.00	0.06

Table VI
Macroeconomic Predictability Regressions

The table presents results of the macroeconomic predictability regressions specified by equation (10). Estimates of the constant terms as well as PC_1 and PC_2 coefficients in Model 3 are not tabulated. The sample period for regressions including IP, CLI and BCI is January 1975 to August 2015 and January 1986 to August 2015 when including EXP or IMP. Point estimates are reported with Newey and West (1987) standard errors using $h - 1$ lags. * and ** indicate significance at the 10 % or 5 % levels, respectively.

		Model 1: Basis			**Model 2: Forward Factor**			**Model 3: PC-Factors**		
Variable	n	$\beta^{(n)}$	$\gamma^{(n)}$	R^2_{adj}	$\beta^{(n)}$	$\gamma^{(n)}$	R^2_{adj}	$\beta_3^{(n)}$	$\gamma^{(n)}$	R^2_{adj}
Panel A: h = 1 month										
IP	1	−0.27	0.71**	1.29	0.86**	0.68**	2.54	1.93**	0.72**	2.39
		(0.33)	(0.32)		(0.32)	(0.30)		(0.72)	(0.32)	
	4	−0.05	0.77**	1.33	0.84**	0.71**	2.80	1.65**	0.76**	2.17
		(0.34)	(0.32)		(0.31)	(0.30)		(0.72)	(0.32)	
CLI	1	−0.31	5.43**	5.87	0.93**	5.37**	7.11	1.72**	5.33**	6.78
		(0.31)	(1.36)		(0.29)	(1.35)		(0.72)	(1.37)	
	4	−0.07	5.32**	5.58	0.92**	5.25**	7.13	1.46**	5.23**	6.30
		(0.33)	(1.37)		(0.29)	(1.37)		(0.72)	(1.38)	
BCI	1	−0.32	4.89**	4.89	0.94**	4.81**	6.11	1.77**	4.80**	5.85
		(0.32)	(1.35)		(0.29)	(1.35)		(0.72)	(1.37)	
	4	−0.08	4.72**	4.47	0.93**	4.65**	6.02	1.50**	4.66**	5.26
		(0.33)	(1.36)		(0.29)	(1.37)		(0.72)	(1.38)	
EXP	1	−0.10	0.16**	1.00	0.82**	0.15**	2.15	1.52*	0.16**	1.49
		(0.34)	(0.08)		(0.31)	(0.07)		(0.77)	(0.08)	
	4	−0.05	0.18**	1.49	0.89**	0.17**	3.15	1.21	0.18**	1.52
		(0.36)	(0.07)		(0.29)	(0.07)		(0.76)	(0.07)	
IMP	1	−0.10	0.14**	1.12	0.83**	0.13**	2.31	1.49*	0.13**	1.56
		(0.34)	(0.06)		(0.31)	(0.05)		(0.77)	(0.06)	
	4	−0.06	0.15**	1.56	0.90**	0.14**	3.30	1.17	0.15**	1.56
		(0.36)	(0.06)		(0.28)	(0.05)		(0.75)	(0.06)	
Panel B: h = 12 months										
IP	1	−2.09	1.94	0.70	0.98**	1.72	1.57	6.02**	1.76	1.31
		(2.60)	(1.95)		(0.35)	(2.05)		(2.97)	(1.99)	
	4	−2.22	2.42	0.95	0.93**	2.33	1.51	3.87	2.41	0.70
		(3.60)	(2.02)		(0.37)	(2.10)		(3.15)	(2.00)	
CLI	1	−2.11	29.12**	8.66	0.97**	28.57**	9.29	4.50*	28.34**	8.86
		(2.47)	(8.63)		(0.32)	(8.81)		(2.69)	(8.46)	
	4	−1.93	31.07**	9.40	0.94**	30.85**	9.90	2.34	30.91**	9.05
		(3.38)	(8.57)		(0.35)	(8.78)		(2.85)	(8.47)	
BCI	1	−2.18	16.93**	3.14	1.00**	16.28**	3.89	5.15*	16.02**	3.51
		(2.50)	(6.79)		(0.34)	(6.93)		(2.93)	(6.83)	
	4	−2.21	18.66**	3.62	0.97**	18.39**	4.16	2.99	18.41**	3.29
		(3.50)	(7.19)		(0.37)	(7.21)		(3.08)	(7.13)	
EXP	1	−1.12	0.01	−0.44	1.05**	−0.02	−0.17	6.11*	−0.02	−0.11
		(2.78)	(0.30)		(0.38)	(0.32)		(3.18)	(0.31)	
	4	−0.50	0.14	−0.51	1.04**	0.08	0.67	3.33	0.14	−0.89
		(3.98)	(0.31)		(0.42)	(0.30)		(3.29)	(0.30)	
IMP	1	−1.12	0.02	−0.44	1.05**	0.00	−0.17	6.11*	−0.02	−0.11
		(2.78)	(0.23)		(0.38)	(0.25)		(3.18)	(0.24)	
	4	−0.53	0.07	−0.53	1.05**	0.04	0.66	3.34	0.07	−0.92
		(3.97)	(0.23)		(0.42)	(0.23)		(3.30)	(0.23)	

Table VII
Out-of-sample Predictability

The table shows R^2_{OOS}s and MSFE-adjusted statistics for commodity return forecasts based on regression model (10). Results are reported for a maturity of 1 and 4 months and a forecasting horizon of 1 month. Out-of-sample forecast using either IP, CLI or BCI are evaluated from January 1985 to August 2015 using an expanding window estimation. Out-of-sample forecasts using EXP or IMP are evaluated from January 1996 to August 2015. * and ** indicate significance at the 10 % or 5 % levels, respectively.

	Model 1: Basis		**Model 2: Forward Factor**		**Model 3: PC-Factors**	
Variable	1	4	1	4	1	4
IP	1.34**	1.72**	−0.53	−0.16	0.58**	−0.10
	(1.97)	(1.92)	(1.87)	(2.05)	(2.68)	(2.30)
CLI	7.60**	7.55**	5.78**	5.77**	6.46**	5.45**
	(3.12)	(2.96)	(3.23)	(3.23)	(3.83)	(3.48)
BCI	6.58**	6.32**	4.52**	4.28**	5.53**	4.22**
	(3.13)	(2.89)	(3.16)	(3.13)	(3.86)	(3.41)
EXP	0.94*	1.26*	−1.69	−0.28	−0.07	0.33*
	(1.44)	(1.54)	(0.99)	(1.59)	(1.41)	(1.34)
IMP	1.33**	1.56**	−1.26	0.09**	0.24*	0.57*
	(1.82)	(1.80)	(1.15)	(1.75)	(1.54)	(1.48)

Table VIII
Baseline regressions with additional predictor variables

The table reports results of the multiple predictive regression model specified by equation (11). Estimates of the constant terms are not tabulated. The sample period is January 1986 to August 2015. Point estimates are reported with Newey and West (1987) standard errors using $h-1$ lags. * and ** indicate significance at the 10 % or 5 % levels, respectively.

		h = 1 month			h = 12 months		
Variable	n	$\beta^{(n)}$	se	R^2_{adj}	$\beta^{(n)}$	se	R^2_{adj}
Model 1: Basis							
basis	1	−0.06	(0.35)	1.72	−6.83**	(2.70)	16.70
volatility		0.03	(0.05)		0.86**	(0.30)	
spot change		0.06	(0.08)		−0.40**	(0.14)	
hedging pressure		0.00	(0.03)		0.16	(0.27)	
open interest		0.48**	(0.21)		4.78**	(1.45)	
volume		−0.08*	(0.05)		−0.01	(0.25)	
basis	4	−0.06	(0.39)	2.93	−6.97	(4.60)	20.00
volatility		0.05	(0.05)		1.09**	(0.34)	
spot change		0.06	(0.08)		−0.38**	(0.18)	
hedging pressure		0.00	(0.03)		0.00	(0.26)	
open interest		0.56**	(0.21)		5.96**	(1.72)	
volume		−0.02	(0.04)		−0.28	(0.20)	
Model 2: Forward Factor							
FW-factor	1	0.58	(0.43)	2.18	1.66	(1.24)	14.15
volatility		0.03	(0.05)		0.75**	(0.31)	
spot change		0.06	(0.08)		−0.33**	(0.14)	
hedging pressure		0.00	(0.03)		0.17	(0.29)	
open interest		0.45**	(0.21)		3.96**	(1.46)	
volume		−0.07	(0.04)		0.01	(0.25)	
FW-factor	4	0.83**	(0.41)	3.90	2.49*	(1.28)	19.56
volatility		0.05	(0.05)		0.97**	(0.34)	
spot change		0.05	(0.08)		−0.33**	(0.15)	
hedging pressure		0.00	(0.03)		0.02	(0.27)	
open interest		0.53**	(0.21)		5.49**	(1.58)	
volume		−0.02	(0.04)		−0.28	(0.20)	
Model 3: PC-Factors							
PC_1	1	−0.07	(0.21)	2.69	−4.79**	(2.33)	19.57
PC_2		0.29	(0.53)		2.29	(3.26)	
PC_3		1.89**	(0.80)		7.84**	(2.88)	
volatility		0.04	(0.05)		0.97**	(0.30)	
spot change		0.06	(0.08)		−0.46**	(0.16)	
hedging pressure		0.00	(0.03)		0.17	(0.25)	
open interest		0.48**	(0.21)		5.06**	(1.48)	
volume		−0.08*	(0.05)		−0.08	(0.24)	
PC_1	4	−0.02	(0.20)	3.28	−3.93	(2.44)	20.09
PC_2		0.05	(0.52)		0.35	(3.17)	
PC_3		1.51*	(0.78)		4.84	(2.98)	
volatility		0.05	(0.05)		1.12**	(0.33)	
spot change		0.06	(0.08)		−0.40**	(0.18)	
hedging pressure		0.01	(0.03)		0.02	(0.25)	
open interest		0.55**	(0.21)		6.21**	(1.77)	
volume		−0.02	(0.04)		−0.29	(0.20)	

Table IX
Lagged macroeconomic predictor variables

The table presents results of the macroeconomic predictability regressions with lagged economic fundamentals given by equation (12). The forecasting horizon is 1 month. Estimates of the constant terms as well as PC_1 and PC_2 coefficients in Model 3 are not tabulated. The sample period for regressions with IP, CLI and BCI is January 1975 to August 2015 and January 1986 to August 2015 when including EXP or IMP. Point estimates are reported with Newey and West (1987) standard errors using $h-1$ lags. * and ** indicate significance at the 10 % or 5 % levels, respectively.

		Model 1: Basis			**Model 2: Forward Factor**			**Model 3: PC-Factors**		
Variable	n	$\beta^{(n)}$	$\gamma^{(n)}$	R^2_{adj}	$\beta^{(n)}$	$\gamma^{(n)}$	R^2_{adj}	$\beta_3^{(n)}$	$\gamma^{(n)}$	R^2_{adj}
Panel A: lag = 1 month										
IP	1	−0.37	0.60*	1.01	0.89**	0.55*	2.20	1.96**	0.60*	2.25
		(0.32)	(0.31)		(0.32)	(0.30)		(0.72)	(0.31)	
	4	−0.08	0.68**	1.00	0.86**	0.61**	2.51	1.67**	0.68**	2.01
		(0.35)	(0.31)		(0.31)	(0.31)		(0.72)	(0.31)	
CLI	1	−0.29	4.70**	4.34	0.92**	4.62**	5.53	1.73**	4.62**	5.27
		(0.32)	(1.26)		(0.30)	(1.25)		(0.72)	(1.26)	
	4	−0.03	4.73**	4.32	0.91**	4.62**	5.78	1.46**	4.65**	5.02
		(0.33)	(1.27)		(0.29)	(1.27)		(0.71)	(1.27)	
BCI	1	−0.30	2.58**	1.24	0.97**	2.51**	2.52	1.87**	2.53**	2.28
		(0.33)	(1.11)		(0.30)	(1.10)		(0.72)	(1.10)	
	4	−0.08	2.69**	1.20	0.96**	2.62**	2.77	1.59**	2.65**	2.01
		(0.34)	(1.12)		(0.30)	(1.12)		(0.72)	(1.11)	
EXP	1	−0.12	0.09	−0.01	0.91**	0.09	1.28	1.68**	0.10	0.69
		(0.35)	(0.09)		(0.32)	(0.09)		(0.78)	(0.09)	
	4	−0.09	0.14	0.70	0.95**	0.13	2.53	1.45*	0.15*	0.98
		(0.37)	(0.09)		(0.30)	(0.08)		(0.77)	(0.09)	
IMP	1	−0.10	0.07	−0.08	0.92**	0.07	1.29	1.65**	0.07	0.55
		(0.35)	(0.06)		(0.31)	(0.06)		(0.78)	(0.06)	
	4	−0.12	0.09	0.27	1.00**	0.09	2.25	1.40*	0.10	0.49
		(0.37)	(0.06)		(0.29)	(0.06)		(0.77)	(0.07)	
Panel B: lag = 3 months										
IP	1	−0.38	0.07	−0.03	1.00**	0.08	1.22	1.99**	0.03	1.17
		(0.32)	(0.32)		(0.32)	(0.31)		(0.73)	(0.33)	
	4	−0.18	0.03	−0.34	1.00**	0.03	1.28	1.71**	−0.01	0.61
		(0.35)	(0.32)		(0.31)	(0.31)		(0.73)	(0.33)	
CLI	1	−0.35	2.97**	1.77	0.94**	2.89**	2.90	1.93**	2.98**	2.98
		(0.32)	(1.17)		(0.30)	(1.16)		(0.72)	(1.15)	
	4	−0.07	3.20**	1.80	0.92**	3.09**	3.25	1.64**	3.19**	2.76
		(0.33)	(1.17)		(0.30)	(1.17)		(0.71)	(1.17)	
BCI	1	−0.38	0.67	0.06	1.00**	0.62	1.27	1.99**	0.69	1.27
		(0.32)	(0.96)		(0.31)	(0.95)		(0.72)	(0.95)	
	4	−0.15	1.03	−0.12	0.97**	0.96	1.43	1.70**	1.04	0.85
		(0.35)	(0.99)		(0.30)	(0.97)		(0.72)	(0.97)	
EXP	1	−0.18	0.03	−0.43	0.98**	0.05	0.98	1.66**	0.03	0.21
		(0.34)	(0.08)		(0.31)	(0.08)		(0.81)	(0.08)	
	4	−0.21	0.02	−0.45	1.08**	0.03	1.59	1.37*	0.02	−0.32
		(0.37)	(0.08)		(0.29)	(0.08)		(0.79)	(0.08)	
IMP	1	−0.15	0.05	−0.27	0.95**	0.05	1.09	1.68**	0.05	0.39
		(0.34)	(0.07)		(0.31)	(0.07)		(0.80)	(0.07)	
	4	−0.20	0.04	−0.31	1.06**	0.04	1.67	1.39*	0.05	−0.16
		(0.37)	(0.06)		(0.29)	(0.06)		(0.79)	(0.06)	

Table X
Baseline regressions during expansion & recessions

The table summarizes results of the state-dependent regression model specified by equation (13). The economic state is defined by the NBER recession indicator. Estimates of the constant terms as well as PC_1 and PC_2 coefficients in Model 3 are not tabulated. The sample period is January 1975 to August 2015. Point estimates are reported with Newey and West (1987) standard errors using $h-1$ lags. * and ** indicate significance at the 10 % or 5 % levels, respectively.

		h = 1 month			h = 12 months		
Variable	n	$\beta^{(n)}$	se	R^2_{adj}	$\beta^{(n)}$	se	R^2_{adj}
Model 1: Basis							
expansion	1	−0.32	(0.32)	1.53	−2.02	(2.93)	5.76
recession		0.58	(1.06)		3.85	(4.42)	
expansion	4	0.12	(0.35)	1.48	−1.62	(3.75)	5.04
recession		−0.52	(1.05)		4.90	(7.11)	
Model 2: Forward Factor							
expansion	1	1.09**	(0.29)	1.36	1.26**	(0.35)	6.63
recession		−0.75	(1.57)		−2.63**	(0.94)	
expansion	4	1.12**	(0.28)	1.58	1.22**	(0.39)	5.58
recession		−1.15	(1.53)		−2.50**	(0.96)	
Model 3: PC-Factors							
expansion	1	1.98**	(0.76)	2.58	6.81**	(3.25)	5.95
recession		−1.17**	(2.56)		−10.92	(6.91)	
expansion	4	1.77**	(0.75)	2.19	4.28	(3.58)	4.46
recession		−1.47	(2.55)		−8.04	(6.65)	

Table XI
Predictability of commodity index returns

The table presents results for predicting monthly returns on the SP-GSCI (Panel A) and the DJ-UBS commodity index (Panel B) using the macroeconomic predictability regression model given by equation (10). Estimates of the constant terms as well as PC_1 and PC_2 coefficients in Model 3 are not tabulated. The sample period for SP-GSCI returns is January 1975 to August 2015 whereas the DJ-UBS index returns only start in January 1991 to August 2015. Point estimates are reported with Newey and West (1987) standard errors using $h-1$ lags. * and ** indicate significance at the 10 % or 5 % levels, respectively.

	Model 1: Basis			**Model 2: Forward Factor**			**Model 3: PC-Factors**		
Variable	β	γ	R^2_{adj}	β	γ	R^2_{adj}	β_3	γ	R^2_{adj}
Panel A: SP-GSCI returns (1975-2015)									
IP	−0.85	1.26**	2.23	1.13**	1.30**	2.58	2.34*	1.28**	2.28
	(0.54)	(0.49)		(0.53)	(0.47)		(1.30)	(0.49)	
CLI	−0.91*	6.81**	4.42	1.33**	6.95**	4.69	2.17*	6.76**	4.37
	(0.52)	(2.24)		(0.50)	(2.21)		(1.31)	(2.26)	
BCI	−0.89*	7.60**	5.53	1.32**	7.70**	5.79	2.15*	7.58**	5.51
	(0.51)	(2.13)		(0.50)	(2.12)		(1.29)	(2.15)	
EXP	−1.02*	0.18	1.18	1.15**	0.19	1.30	2.62*	0.19	1.21
	(0.58)	(0.13)		(0.57)	(0.12)		(1.41)	(0.13)	
IMP	−1.01*	0.15*	1.25	1.15**	0.16*	1.35	2.53*	0.15*	1.22
	(0.58)	(0.09)		(0.57)	(0.09)		(1.41)	(0.09)	
Panel B: DJ-UBS returns (1991-2015)									
IP	−0.41	1.28**	3.07	0.44	1.29**	3.27	1.64	1.34**	3.07
	(0.52)	(0.46)		(0.59)	(0.45)		(1.23)	(0.46)	
CLI	−0.39	7.63**	8.86	0.72	7.63**	9.04	1.07	7.59**	8.46
	(0.50)	(2.00)		(0.54)	(1.96)		(1.25)	(2.03)	
BCI	−0.37	8.39**	9.89	0.66	8.36**	9.97	1.03	8.42**	9.60
	(0.49)	(2.01)		(0.53)	(1.98)		(1.22)	(2.04)	
EXP	−0.53	0.15	0.40	0.75	0.15	0.59	1.64	0.16	0.15
	(0.52)	(0.12)		(0.57)	(0.12)		(1.22)	(0.12)	
IMP	−0.47	0.26**	1.78	0.61	0.26**	2.00	1.54	0.26**	1.55
	(0.52)	(0.11)		(0.57)	(0.10)		(1.21)	(0.11)	

Table XII
Sector Analysis: baseline regressions

The table gives results of the baseline regressions specified by equations (4), (7) and (9), which are estimated for each commodity sector. Estimates of the constant terms are not tabulated. The sample period for Grains, Livestock and Softs is January 1975 to August 2015, whereas for Energy and Metals it is January 1986 to August 2015. Point estimates are reported with Newey and West (1987) standard errors using $h-1$ lags. * and ** indicate significance at the 10 % or 5 % levels, respectively.

		M1: Basis		M2: FW-Factor		M3: PC-Factors			
Sector	n	$\beta^{(n)}$	R^2_{adj}	$\beta^{(n)}$	R^2_{adj}	$\beta^{(n)}_1$	$\beta^{(n)}_2$	$\beta^{(n)}_3$	R^2_{adj}
Panel A: h = 1 month									
Energy	1	−0.46	0.31	1.07**	4.91	−0.22	1.06	0.73	−0.04
		(0.36)		(0.31)		(0.20)	(0.96)	(2.79)	
	4	−0.34	0.04	0.94**	5.13	−0.19	0.54	1.82	−0.07
		(0.36)		(0.25)		(0.17)	(0.83)	(2.47)	
Grains	1	0.29	0.03	1.13**	1.32	0.38	0.56	−1.11	1.08
		(0.34)		(0.53)		(0.24)	(0.42)	(0.89)	
	4	0.73*	0.72	0.81*	0.73	0.29	0.45	−0.85	0.48
		(0.38)		(0.47)		(0.21)	(0.39)	(0.79)	
Livestock	1	−0.17	0.13	1.09**	1.36	−0.03	0.22	−0.25	−0.05
		(0.14)		(0.39)		(0.08)	(0.19)	(0.35)	
	4	0.05	−0.16	0.95**	0.79	−0.01	0.20	−0.13	−0.15
		(0.11)		(0.33)		(0.07)	(0.16)	(0.27)	
Metals	1	−1.02	−0.08	0.97**	2.29	−1.63**	−2.28*	−0.73	1.42
		(1.11)		(0.27)		(0.61)	(1.28)	(2.03)	
	4	−3.66**	3.05	1.11**	3.11	−1.99**	−3.31**	0.97	2.75
		(0.89)		(0.28)		(0.64)	(1.27)	(1.80)	
Softs	1	0.24	−0.04	0.98*	0.59	0.09	−0.31	0.02	−0.43
		(0.31)		(0.51)		(0.18)	(0.43)	(0.47)	
	4	0.03	−0.20	1.04**	0.96	0.07	−0.48	0.17	−0.21
		(0.29)		(0.45)		(0.16)	(0.40)	(0.48)	
Panel B: h = 12 months									
Energy	1	−2.75	0.90	1.04**	2.40	−1.50	1.59	4.71	0.39
		(2.33)		(0.35)		(1.40)	(4.76)	(14.93)	
	4	−3.06	1.09	0.96**	2.51	−1.46	−1.29	6.08	0.67
		(2.84)		(0.31)		(1.24)	(4.45)	(12.13)	
Grains	1	0.12	−0.21	1.08	0.54	0.40	1.36	−5.52**	0.52
		(1.23)		(0.92)		(1.19)	(1.22)	(1.68)	
	4	1.99	0.33	0.86	0.11	0.59	1.18	−4.80**	0.28
		(2.46)		(0.90)		(1.22)	(1.24)	(1.69)	
Livestock	1	−2.08**	3.27	0.99**	5.28	−1.47**	0.66	2.33**	6.12
		(0.69)		(0.35)		(0.48)	(0.86)	(1.15)	
	4	−1.87**	3.51	1.06**	3.18	−1.15**	0.06	2.18**	4.54
		(0.77)		(0.30)		(0.42)	(0.69)	(1.10)	
Metals	1	−16.05*	2.04	0.96**	8.66	−19.06**	−20.21**	12.37	11.90
		(8.96)		(0.38)		(6.25)	(5.65)	(14.13)	
	4	−41.44**	16.65	1.07**	11.36	−23.03**	−25.60**	22.06	15.26
		(10.20)		(0.44)		(6.63)	(5.95)	(17.57)	
Softs	1	0.21	−0.20	1.18**	0.91	−0.62	−2.19	1.10	−0.05
		(1.49)		(0.52)		(1.25)	(2.05)	(1.95)	
	4	−0.48	−0.19	0.99*	0.53	−0.23	−1.38	1.42	−0.40
		(2.51)		(0.54)		(1.31)	(2.16)	(2.09)	

Table XIII
Sector Analysis: macroeconomic predictability regressions

The table presents results of the macroeconomic predictability regression model specified in equation (10) and estimated for commodity sector returns. The forecasting horizon and maturity is 1 month. Estimates of the constant terms are not tabulated. The sample period for Grains, Livestock and Softs is January 1975 to August 2015, whereas for Energy and Metals it is January 1986 to August 2015. Point estimates are reported with Newey and West (1987) standard errors using $h-1$ lags. * and ** indicate significance at the 10 % or 5 % levels, respectively.

	M1: Basis			**M2: FW-Factor**			**M3: PC-Factors**				
Variable	$\beta^{(n)}$	$\gamma^{(n)}$	R^2_{adj}	$\beta^{(n)}$	$\gamma^{(n)}$	R^2_{adj}	$\beta_1^{(n)}$	$\beta_2^{(n)}$	$\beta_3^{(n)}$	$\gamma^{(n)}$	R^2_{adj}
Panel A: Energy											
IP	−0.37	1.95**	1.83	0.98**	1.82**	6.29	−0.16	1.02	0.01	1.95**	1.46
	(0.35)	(0.75)		(0.31)	(0.72)		(0.20)	(0.96)	(2.79)	(0.76)	
CLI	−0.56*	10.11**	3.55	1.09**	10.09**	8.16	−0.27	0.93	−0.82	10.11**	3.11
	(0.34)	(3.43)		(0.32)	(3.32)		(0.19)	(0.94)	(2.81)	(3.54)	
BCI	−0.57*	12.77**	5.12	1.05**	12.10**	9.22	−0.28	0.96	−0.64	12.74**	4.69
	(0.33)	(3.32)		(0.32)	(3.35)		(0.19)	(0.94)	(2.82)	(3.40)	
EXP	−0.40	0.33	0.91	1.01**	0.30	5.41	−0.17	1.18	0.70	0.34*	0.64
	(0.35)	(0.20)		(0.31)	(0.18)		(0.20)	(0.96)	(2.76)	(0.20)	
IMP	−0.35	0.35**	1.56	0.99**	0.33**	6.03	−0.15	1.06	0.67	0.36**	1.24
	(0.35)	(0.15)		(0.31)	(0.14)		(0.20)	(0.98)	(2.75)	(0.15)	
Panel B: Grains											
IP	0.28	0.58	0.15	1.18**	0.63	1.55	0.38	0.59	−1.07	0.64	1.25
	(0.34)	(0.53)		(0.54)	(0.50)		(0.24)	(0.42)	(0.89)	(0.53)	
CLI	0.34	5.44**	2.00	1.32**	5.88**	3.64	0.44*	0.61	−1.10	5.80**	3.34
	(0.33)	(2.06)		(0.52)	(2.12)		(0.23)	(0.41)	(0.87)	(2.11)	
BCI	0.33	4.55**	1.40	1.32**	5.07**	3.05	0.44*	0.62	−1.13	4.99**	2.75
	(0.34)	(2.03)		(0.53)	(2.09)		(0.23)	(0.41)	(0.87)	(2.08)	
EXP	0.49	0.18	0.71	1.01*	0.17	1.53	0.44	0.24	0.22	0.17	0.87
	(0.41)	(0.14)		(0.60)	(0.13)		(0.27)	(0.47)	(1.12)	(0.14)	
IMP	0.47	0.09	0.33	1.00*	0.08	1.15	0.44	0.26	0.17	0.09	0.51
	(0.41)	(0.10)		(0.60)	(0.09)		(0.27)	(0.46)	(1.11)	(0.10)	
Panel C: Livestock											
IP	−0.17	0.39	0.19	1.03**	0.37	1.41	−0.03	0.23	−0.25	0.40	0.03
	(0.15)	(0.36)		(0.40)	(0.35)		(0.08)	(0.19)	(0.35)	(0.36)	
CLI	−0.15	2.41*	0.67	1.08**	2.54*	1.99	−0.02	0.22	−0.28	2.53*	0.57
	(0.14)	(1.40)		(0.39)	(1.41)		(0.08)	(0.18)	(0.35)	(1.37)	
BCI	−0.15	2.56*	0.79	1.08**	2.67*	2.10	−0.01	0.22	−0.27	2.68**	0.69
	(0.14)	(1.35)		(0.39)	(1.36)		(0.08)	(0.18)	(0.35)	(1.33)	
EXP	−0.31**	0.03	0.53	1.14**	0.04	2.09	−0.06	0.33*	−0.28	0.04	0.25
	(0.14)	(0.08)		(0.38)	(0.08)		(0.08)	(0.18)	(0.36)	(0.08)	
IMP	−0.31**	0.00	0.49	1.16**	0.00	2.03	−0.06	0.33*	−0.27	0.00	0.20
	(0.15)	(0.06)		(0.38)	(0.06)		(0.08)	(0.18)	(0.36)	(0.06)	
Panel D: Metals											
IP	−1.25	0.87*	0.73	0.93**	0.81*	3.02	−1.73**	−2.08	−0.65	0.87*	2.25
	(1.12)	(0.50)		(0.25)	(0.46)		(0.62)	(1.32)	(2.08)	(0.50)	
CLI	−0.55	10.17**	10.52	0.84**	9.93**	12.36	−1.21**	−2.09*	−0.51	9.87**	11.38
	(1.01)	(1.88)		(0.24)	(1.90)		(0.58)	(1.25)	(2.02)	(1.90)	
BCI	−0.93	8.88**	7.18	0.97**	8.91**	9.59	−1.51**	−2.20*	−0.29	8.74**	8.47
	(1.05)	(2.00)		(0.24)	(2.01)		(0.59)	(1.27)	(2.19)	(1.99)	
EXP	−1.09	0.10	−0.13	0.96**	0.10	2.30	−1.67**	−2.23*	−0.78	0.10	1.41
	(1.12)	(0.11)		(0.26)	(0.11)		(0.62)	(1.31)	(2.08)	(0.11)	
IMP	−1.01	0.07	−0.18	0.96**	0.08	2.27	−1.67**	−2.38*	−0.99	0.09	1.47
	(1.11)	(0.09)		(0.26)	(0.08)		(0.62)	(1.30)	(2.10)	(0.09)	
Panel E: Softs											
IP	0.26	0.87**	0.95	0.78	0.84**	1.46	0.15	−0.20	0.05	0.88**	0.54
	(0.30)	(0.37)		(0.51)	(0.36)		(0.18)	(0.43)	(0.48)	(0.37)	
CLI	0.24	5.86**	3.66	0.88*	5.79**	4.20	0.12	−0.23	−0.17	5.89**	3.29
	(0.28)	(1.53)		(0.49)	(1.51)		(0.17)	(0.41)	(0.49)	(1.54)	
BCI	0.20	5.16**	2.88	0.88*	5.11**	3.45	0.09	−0.23	−0.18	5.19**	2.51
	(0.29)	(1.48)		(0.49)	(1.47)		(0.17)	(0.41)	(0.49)	(1.50)	
EXP	−0.14	0.16*	0.29	0.84	0.16*	0.77	0.02	0.30	−0.11	0.16*	−0.19
	(0.31)	(0.10)		(0.80)	(0.09)		(0.22)	(0.44)	(0.51)	(0.10)	
IMP	−0.19	0.15*	0.51	0.85	0.15*	0.97	0.01	0.37	−0.14	0.15*	0.07
	(0.30)	(0.08)		(0.79)	(0.08)		(0.22)	(0.43)	(0.50)	(0.08)	

Table XIV
Sector Analysis: out-of-sample predictability

The table shows R^2_{OOS}s and MSFE-adjusted statistics for commodity sector return forecasts based on regression model (10). The forecasting horizon is 1 month. Out-of-sample forecasts for Grains, Livestock and Softs are evaluated from January 1985 to August 2015, whereas forecasts for Energy and Metals from January 1996 to August 2015, using and expanding window estimation. * and ** indicate significance at the 10 % or 5 % levels, respectively.

	M1: Basis		**M2: FW-Factor**		**M3: PC-Factors**	
Variable	1	4	1	4	1	4
Panel A: Energy						
IP	2.07**	1.91**	−1.21	−0.50	1.43**	1.68**
	(1.95)	(1.82)	(1.36)	(1.54)	(1.76)	(1.77)
CLI	4.05**	4.89**	0.33*	2.49**	2.60**	4.30**
	(2.21)	(2.37)	(1.63)	(2.12)	(1.88)	(2.25)
BCI	6.61**	7.80**	1.90**	4.43**	5.29**	7.40**
	(2.51)	(2.67)	(1.93)	(2.39)	(2.31)	(2.61)
EXP	0.47	0.38	−2.69	−1.66	−0.15	0.40
	(0.82)	(0.78)	(0.41)	(0.81)	(0.53)	(0.86)
IMP	1.88**	1.98**	−1.35	−0.18	1.24*	1.85**
	(1.80)	(1.81)	(0.87)	(1.32)	(1.52)	(1.76)
Panel B: Grains						
IP	−0.49	1.07*	−2.76	−1.59	−1.99	−1.14
	(0.08)	(1.48)	(0.01)	(0.35)	(0.70)	(0.77)
CLI	1.10**	2.16**	−1.45	−0.77	−0.02	0.43**
	(1.65)	(2.12)	(1.27)	(1.24)	(1.87)	(1.75)
BCI	0.58*	1.61**	−2.13	−1.42	−0.76	−0.26
	(1.33)	(1.90)	(0.88)	(0.90)	(1.58)	(1.48)
EXP	−0.30	0.58	−2.39	−1.96	−1.55	−1.22
	(0.42)	(1.04)	(−0.65)	(−0.39)	(0.13)	(0.22)
IMP	−0.59	0.28	−2.66	−2.33	−1.83	−1.57
	(−0.05)	(0.83)	(−1.23)	(−1.02)	(−0.19)	(−0.15)
Panel C: Livestock						
IP	0.38*	0.24	−1.08	−0.16	−0.72	−0.20
	(1.45)	(0.91)	(1.02)	(1.46)	(0.26)	(0.89)
CLI	−0.44	−0.05	−0.83	−0.26	−1.59	−0.55
	(0.86)	(1.01)	(1.52)	(1.63)	(0.64)	(0.98)
BCI	0.58*	0.08	0.10**	−0.29	−0.41	−0.39
	(1.44)	(0.83)	(1.75)	(1.46)	(1.01)	(0.79)
EXP	0.32*	−1.18	−3.14	−2.97	−2.22	−2.32
	(1.35)	(−0.65)	(0.26)	(−0.04)	(−0.31)	(−0.34)
IMP	0.11	−1.64	−3.47	−3.66	−2.42	−2.77
	(1.02)	(−1.13)	(0.21)	(−0.28)	(−0.44)	(−0.59)
Panel D: Metals						
IP	0.52*	3.11**	1.63**	2.68**	0.57**	1.74**
	(1.38)	(3.12)	(2.39)	(2.81)	(2.16)	(2.68)
CLI	12.80**	14.19**	13.50**	14.40**	12.15**	13.16**
	(3.55)	(4.24)	(3.90)	(4.15)	(3.85)	(4.11)
BCI	9.20**	11.95**	10.19**	12.06**	8.82**	10.86**
	(3.27)	(4.17)	(3.79)	(4.09)	(3.70)	(4.01)
EXP	−0.29	2.63**	1.06**	2.56**	−0.20	1.51**
	(−0.20)	(2.76)	(1.75)	(2.53)	(1.57)	(2.41)
IMP	−0.07	3.11**	1.21**	2.92**	0.18**	2.09**
	(0.04)	(2.95)	(1.86)	(2.75)	(1.73)	(2.63)
Panel E: Softs						
IP	−0.30	0.20*	−1.27	−0.23	−1.38	−0.84
	(1.52)	(1.41)	(0.93)	(1.56)	(0.96)	(1.28)
CLI	3.56**	2.87**	2.42**	2.64**	2.47**	1.96**
	(3.04)	(2.63)	(2.65)	(2.87)	(2.67)	(2.44)
BCI	3.18**	2.54**	1.95**	2.24**	1.95**	1.48**
	(2.98)	(2.49)	(2.44)	(2.72)	(2.42)	(2.11)
EXP	−0.22	0.56	−1.14	−0.38	−1.58	−1.18
	(0.52)	(1.27)	(0.03)	(1.10)	(−0.50)	(0.58)
IMP	0.26	0.61*	−0.73	−0.49	−1.06	−1.09
	(1.00)	(1.34)	(0.28)	(0.92)	(−0.10)	(0.38)

Figure 1. Commodity yield curve

This figure shows the futures curve of an aggregate commodity portfolio at the end of December 2008 (red line) and the end of April 2014 (blue line). These dates are classified as recession and expansion periods by the NBER business cycle dating. IP growth refers to the 12-month growth rate of world industrial production at these two dates.

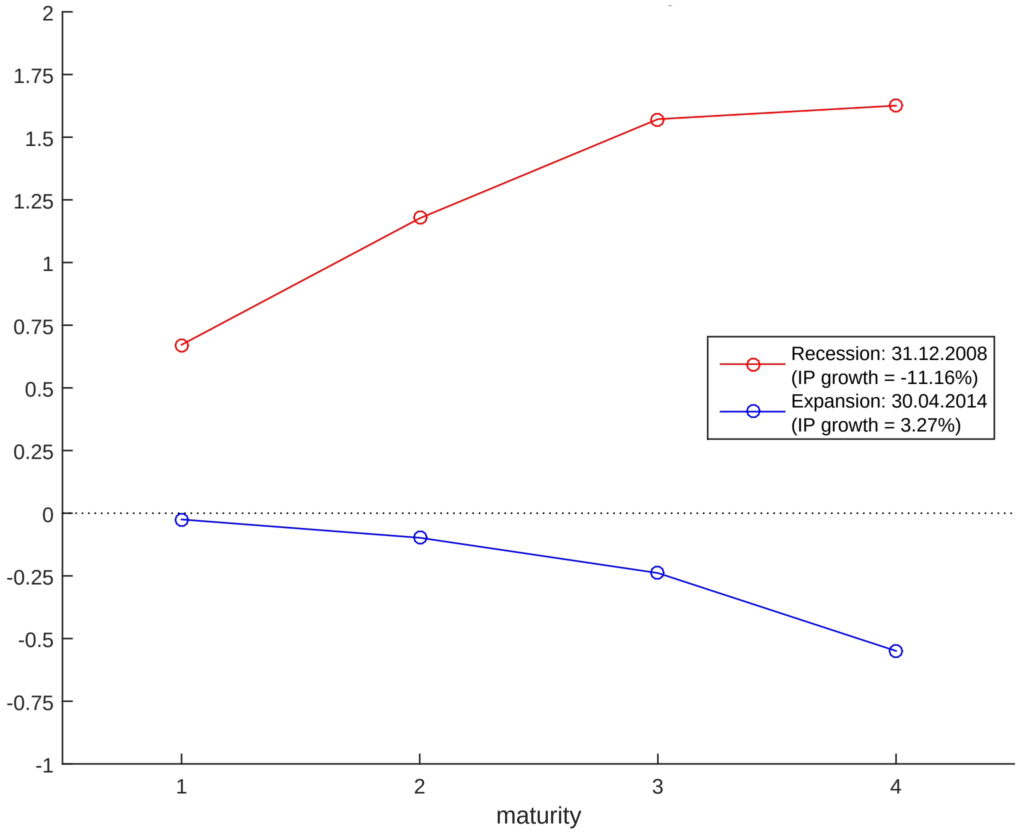

Figure 2. Aggregate commodity basis

The figure shows the basis of an aggregate commodity portfolio for maturities of 1 (red) and 4 (blue) months to delivery. The sample period is January 1975 to August 2015.

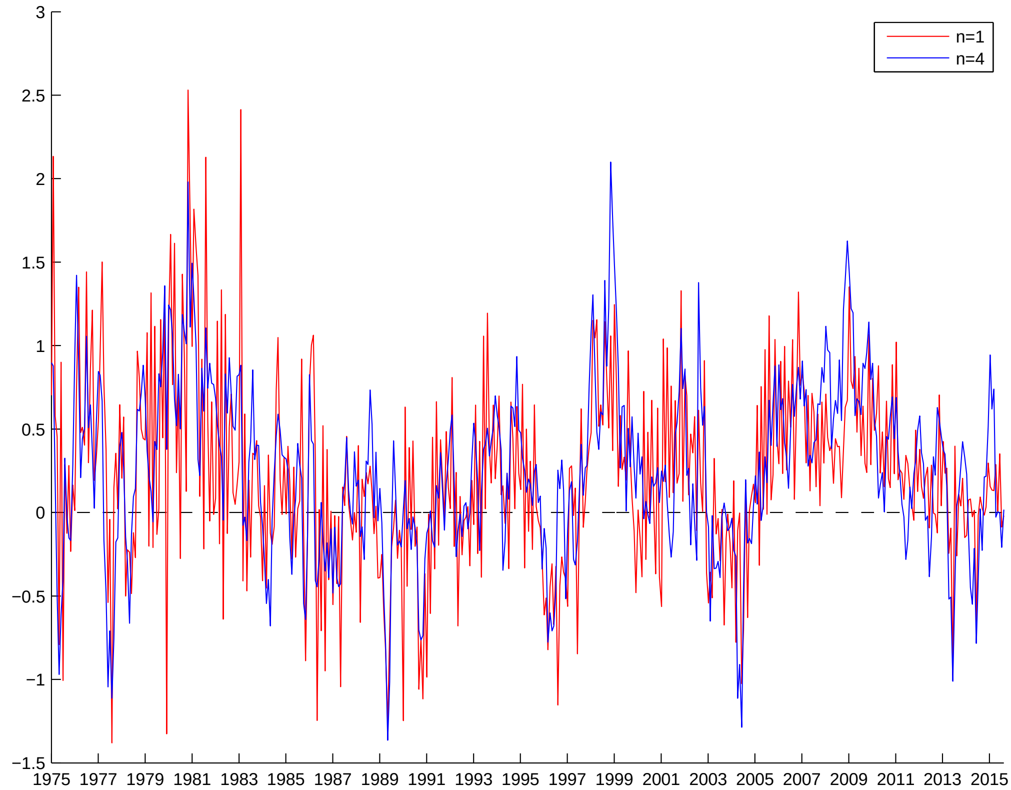

Figure 3. PCA of aggregate commodity basis

The figure shows factor loadings arising from a principal component analysis applied to the aggregate commodity basis of different maturities.

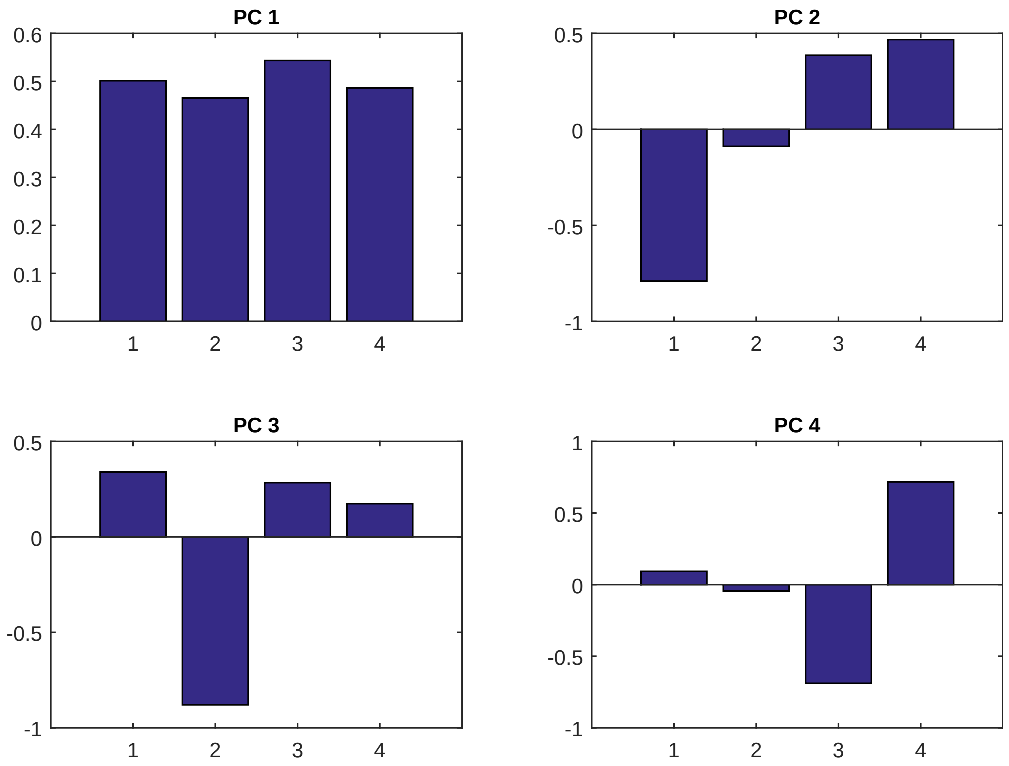

Figure 4. Slope coefficients of unrestricted forward rates regressions

The figure shows the slope coefficients, except the intercept, of the unrestricted regressions given by equation (8) plotted against the maturity of the corresponding forward rate. Each line refers to a different maturity of forecasted aggregate commodity returns. The regressions are run over a sample period from January 1975 to August 2015.

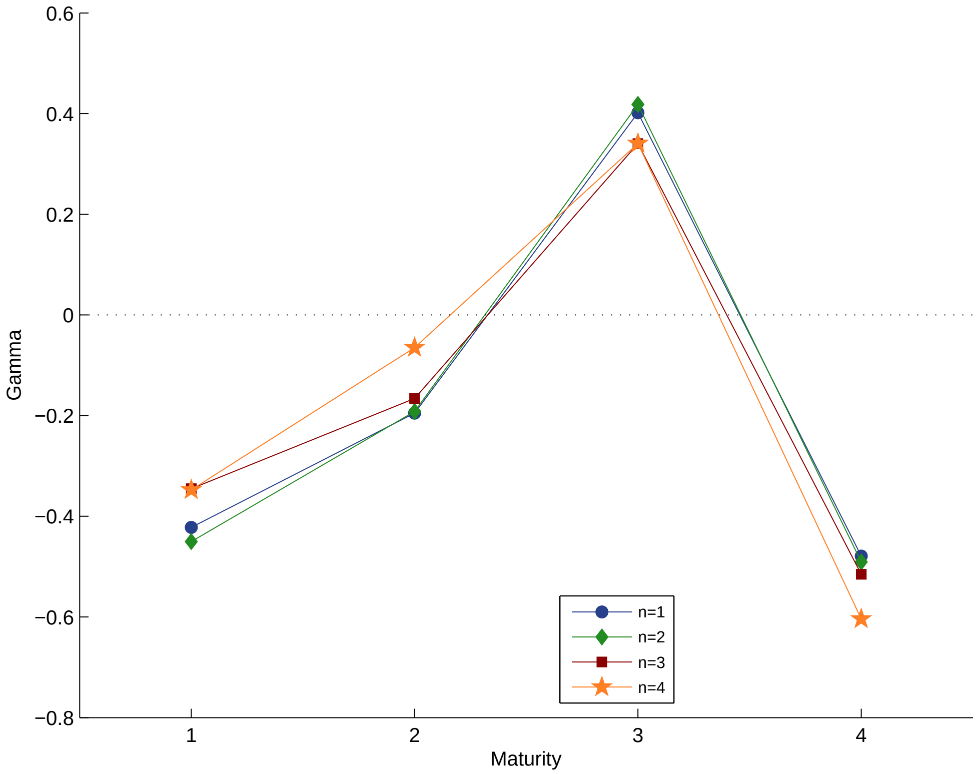

Figure 5. Forecasting performance over time

The figure shows the cumulative difference in squared forecast errors (CDSFE) for the regression model (10), using either industrial production (IP) or the composite leading indicator (CLI) together with each of the three baseline predictors. The model based forecasts are compared to the historical average benchmark. The results range from January 1985 to August 2015.