Predictive Dynamics in Commodity Prices*

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June 26, 2012

Abstract

Using a sample of commodity spot price indexes over the period 1947-2010, we examine predictability of commodity returns at the monthly, quarterly, and annual horizons. We establish out-of-sample predictability by means of variables such as bond spreads, growth in money supply and industrial production. Predictability is strongest for raw industrials and metals indexes and weakest for foods and textiles. Some variables, such as the inflation rate, have little or no predictive power at the monthly horizon, but appear to have stronger predictive power over commodity spot prices at the quarterly and annual horizons. Our results suggest that predictability of commodity returns from macroeconomic variables such as inflation, industrial production and money supply is stronger during economic recessions than during expansions. This finding carries over to models for realized commodity volatility, where economic state variables add predictive power to a simple autoregression mostly during recessions.

Key words: predictability of commodity spot prices, out-of-sample forecast performance, state-dependent predictability.

*Timmermann acknowledges support from CREATES, funded by the Danish National Research Foundation.

1 Introduction

Commodity markets have gained significant investor interest in recent years. According to the Investment Company Institute, total net assets of commodity exchange traded funds grew from \$1bn in 2004 to more than \$100bn in 2010.[1] Commodity markets, particularly those for precious metals, have also been proposed as a vehicle for hedging investors' exposure to inflation risk. This has featured prominently recently due to central bank implementation of quantitative easing policies combined with increased uncertainty about future inflation rates. Increases in commodity prices, notably crude oil, have also been linked to economic recessions and deterioration in growth prospects.[2]

With few exceptions, however, little is known about the extent to which commodity prices are predictable and how they co-vary with economic state variables. Bessembinder and Chan (1992) find that T-bill yields, the dividend yield and the junk bond premium have limited predictive power over movements in agricultural, metals and currency futures prices. Hong and Yogo (2011) find evidence of limited in-sample predictability of commodity spot and futures returns. While predictability of commodity prices has thus been studied by previous authors, several unexamined questions remain.

First, previous studies were concerned with in-sample predictability of commodity prices. However, as pointed out by studies of stock market return predictability, in-sample predictability is not synonymous with the ability to predict returns out-of-sample given the historically available sample information, see, e.g., Pesaran and Timmermann (1995) and Goyal and Welch (2008). Specifically, there is no guarantee that in-sample return predictability could have been used in real time by investors to produce more accurate forecasts of commodity prices than a simple constant return benchmark model.

Second, the commodity price literature has mostly considered predictor variables identified in the literature on predictability of stock and bond returns. Broader measures of macroeconomic risk have not been examined to the same extent. This is important since such variables could well provide good measures of either production or storage costs or, alternatively, time-varying risk premia, both of which could induce predictability in commodity spot price changes.

Third, the literature on predictability of commodity prices has not considered the extent to which such return predictability varies over the economic cycle. This is an important shortcoming

[1]2011 Investment Company Fact Book, 51st Edition.

[2]Hamilton (2011) notes that ten of eleven postwar recessions were preceded by sharp increases in the price of crude petroleum.

given the evidence in Rapach, Strauss and Zhou (2010) and Henkel, Martin, and Nardari (2011) that predictability of stock returns is largely confined to economic recessions. One interpretation of this finding is that expected returns vary more during economic recessions than during expansions. Clearly it is of interest to see if a similar finding carries over to commodity markets for which the state of the economy can be expected to play an important role.

Fourth, much of the work on predictability of commodity price movements has focused on futures prices, while spot prices have received less attention. Spot prices are of separate interest, however, as they affect producer costs and, in turn, price inflation. Moreover, spot and futures prices can be expected to be affected by similar risk premium variations. For example, Acharya et al. (2011) propose a model in which producers' hedging demand induces a common component in spot and futures prices. Speculators are assumed to be liquidity constrained and so producers' hedging demand affect optimal inventory holdings and equilibrium spot prices. In their model, expected spot prices reflect a common risk term as well as inventory stock-out and supply effects. Empirically, Acharya et al. (2011) find mild evidence of predictability of petroleum spot returns from fundamental hedging demand variables as well as from the term spread.

Our paper makes several contributions. First, we explore out-of-sample return predictability for a range of commodity spot price indexes over the 20-year period 1991-2010. In so doing, we consider a wider set of predictors, including macro variables measuring the state of the economy such as inflation, money supply growth, growth in industrial production and changes in the unemployment rate. We separately consider predictability at the monthly, quarterly, and annual horizons and in different economic states.

We find that out-of-sample return predictability varies considerably across different horizons. Specifically, there is modest evidence of out-of-sample predictability of monthly movements in metals and raw industrials commodity spot price indexes as well as for the aggregate commodity spot price index. Specifically, individual predictor variables such as the T-bill rate, the default return spread (the return difference between long-term corporate and government bonds), and money supply growth appear able to predict commodity prices at the monthly frequency. At longer horizons, the evidence on out-of-sample commodity price predictability strengthens considerably. For example, at the quarterly horizon, variables such as the T-bill rate, investment-capital ratio, money supply growth and also the rate of inflation have some predictive power over changes in raw industrials and metals spot prices. At the annual horizon, the evidence is even stronger with a host of similar predictor variables apparently capable of predicting movements in commodity prices. Interestingly, the estimated coefficient on inflation is negative, suggesting that current inflation is negatively related to future commodity price movements.

Second, we find that the only variable capable of consistently predicting commodity spot price movements at both the monthly, quarterly, and annual horizons is the growth in the narrow money supply, M1. Moreover, this variable proved successful at predicting the recent surge in commodity prices following the global financial crisis and the ensuing expansionary monetary policy.

Third, return predictability is notably stronger for the raw industrials and metals indexes and weaker for foods, fats-oils, livestock, and textile indexes.

Fourth, whereas there is little evidence of predictability of commodity prices during expansion periods, there is stronger evidence that some macrovariables predict commodity price movements during recessions. For example, this holds for inflation which fails to predicts commodity price movements in expansions, whereas its predictive power over commodity returns is far stronger during recessions. Similar findings hold for growth in industrial production and money supply growth.

Fifth, and finally, we consider predictability of the realized (log-) commodity volatility. Few, if any, state variables appear capable of improving upon the out-of-sample predictive accuracy of an AR(1) model for commodity volatility. Interestingly, however, during economic recessions several variables, most notably the macroeconomic variables (growth in industrial production, money supply growth, and changes in the unemployment rate), produce better out-of-sample forecasts of monthly commodity market volatility when added to the AR(1) model. The evidence is weaker at the quarterly and annual horizons, although at the quarterly horizon the inflation rate produces notably better out-of-sample forecasts of commodity market volatility in recessions when added to the AR(1) model. We also find that the variables that are capable of predicting increasing commodity prices are different from those predicting price declines. Specifically, whereas lagged volatility, lagged returns, and the lagged money supply growth proved capable of predicting the magnitude of increases in commodity prices, the inflation rate plays a much more prominent role when it comes to predicting the magnitude of declines in commodity prices, decreasing inflation being linked to lower expected commodity prices.

The outline of the paper is as follows. Section 2 introduces the data. Section 3 presents empirical results for univariate models used to capture predictability of movements in commodity spot prices associated with individual predictor variables. Section 4 explores predictability from multivariate predictability models. Section 5 analyses predictability of commodity price volatility and separately considers price decreases versus increases. Finally, Section 6 concludes.

2 Data

This section describes the data sources for the commodity prices and predictor variables and provides a brief characterization of our data.

2.1 Commodity prices

Commodity spot prices are measured by the Reuters/Jeffries-CRB indexes compiled by the Commodity Research Bureau. These are computed as an unweighted geometric mean of the individual commodity prices relative to their base periods which reduces the impact of extreme movements in individual commodity prices in the index. We use end-of-month prices measured at close, denominated in US dollars. When available, the spot price is based on the listed exchange price for a commodity of standard quality but bid or ask prices are used if a spot price is not readily available. The sample period is 1947m1-2010m12.[3]

The data comprises an aggregate spot market index (ticker: CMCRBSPD) that is based on 22 individual commodities. This broad index is split into two major indexes, namely raw industrials (CMCRBIND, including burlap, copper scrap, cotton, hides, lead scrap, print cloth, rosin, rubber, steel scrap, tallow, tin, wool tops, and zinc), and foodstuffs (CMCRBFOD, including butter, cocoa beans, corn, cottonseed oil, hogs, lard, steers, sugar, and wheat). In turn, these indexes are subdivided into metals (CMCRBMED, including copper scrap, lead scrap, steel scrap, tin, and zinc), textiles and fibers (CMCRBTXD, including burlap, cotton, print cloth, and wool tops), fats and oils (CMCRBFAD, including butter, cottonseed oil, lard, and tallow), and livestock and products (CMCRBLID, including hides, hogs, lard, steers, and tallow).

2.2 Predictor variables

As predictors we consider a set of 11 state variables. The first seven variables are from the literature on stock return predictability and was previously used by Goyal and Welch (2008). Specifically, the *Dividend Price Ratio (dp),* is measured as the difference between the log of the 12-month moving sum of dividends and the log of the S&P 500 index; *Treasure Bill (tbl),* is the 3-Month Treasury Bill (secondary market) rate; *Long Term Rate of Returns (ltr)* is the long-term rate of returns on US Bonds; *Term Spread (tms)* is the difference between the long term yield on government bonds and the Treasury Bill rate; *Default Return Spread (dfr)* is the difference between long-term corporate bond and long-term government bond returns; *Inflation (infl)* is the (log) growth of the Consumer Price Index (All Urban Consumers); *Investment to Capital Ratio (ik)* is the ratio of aggregate

[3]For further detail, see http://www.crbtrader.com/crbindex/spot_background.asp.

investments to aggregate capital for the whole economy. These series have been constructed by Goyal & Welch (2008) and are available on the authors' web site.

To measure the broad state of the economy, we consider a range of macroeconomic variables. *Industrial Production (ΔIND)* is the monthly growth in Industrial Production as reported by the Federal Reserve Bank of St. Louis (FRED mnemonic: INDPRO). Quarterly and annual series are obtained averaging monthly values over each quarter and year. For example, letting $IND_{Y2:M2}$ and $IND_{Y2:Q2}$ denote industrial production during the second month and second quarter of the second year in the sample, monthly, quarterly and annual growth rates are computed as follows

$$\begin{aligned} \Delta IND_{Y2:M2} &= ln(IND_{Y2:M2}) - ln(IND_{Y2:M1}) \\ \Delta IND_{Y2:Q2} &= ln\left(\sum_{j=4}^{6} IND_{Y2:Mj}\right) - ln\left(\sum_{i=1}^{3} IND_{Y2:Mi}\right) \\ \Delta IND_{Y2} &= ln\left(\sum_{j=1}^{12} IND_{Y2:Mj}\right) - ln\left(\sum_{i=1}^{12} IND_{Y1:Mi}\right) \end{aligned} \tag{1}$$

Unemployment (ΔUN), is the change in the monthly unemployment rate (FRED mnemonic: UNRATE); quarterly and annual series are obtained averaging monthly values over each quarter and year. Monthly, quarterly and annual growth rates are computed as for Industrial production. *Money Stock ($\Delta M1$),* is the year-on-year growth in the monthly M1 money stock (FRED mnemonic: M1SL), with quarterly and annual series again obtained by averaging monthly values over each quarter and year:

$$\begin{aligned} \Delta M1_{Y2:M2} &= ln(M1_{Y2:M2}) - ln(M1_{Y1:M2}) \\ \Delta M1_{Y2:Q2} &= ln\left(\sum_{j=1}^{3} M1_{Y2:Mj}\right) - ln\left(\sum_{i=1}^{3} M1_{Y1:Mi}\right) \\ \Delta M1_{Y2} &= ln\left(\sum_{j=1}^{12} M1_{Y2:Mj}\right) - ln\left(\sum_{i=1}^{12} M1_{Y1:Mi}\right) \end{aligned} \tag{2}$$

In addition to these variables, we construct a realized commodity price volatility measure. *Commodity volatility (cvol),* is the square root of the sum of squared daily returns on the Dow Jones-AIG Commodity Index available from Global Financial Data (mnemonic: DJCD) over the months, quarters and years according to the adopted frequency:[4]

$$cvol_{Y1:M2} = \sqrt{\sum_{t\in Y1:M2} r_t^2} \quad cvol_{Y1:Q2} = \sqrt{\sum_{t\in Y1:Q2} r_t^2} \quad cvol_{Y1} = \sqrt{\sum_{t\in Y1} r_t^2}. \tag{3}$$

[4]We use the Dow Jones-AIG index, rather than the Reuters/Jeffries-CRB index, because the latter does not have complete daily return records going back to 1947.

2.3 Data Characteristics

Figure 1 presents plots of the nominal commodity spot prices for the seven indexes. Many of the indexes underwent sharp increases during 1973 following the concurrent spike in oil prices. This was followed by more stable nominal prices until 2006, at which point prices rose sharply until mid-2008, only to decline dramatically (with exception of textiles) during the global financial crisis. Between March 2009 and the end of our sample (2010), commodity prices recovered sharply.

Figure 2 shows the associated monthly commodity returns. Percentage price changes from holding a commodity from the end of period t to the end of period $t+1$ is computed as $r_{t+1} = (P_{t+1} - P_t)/P_t$, where P_t and P_{t+1} are the associated commodity prices. Periods of high volatility clearly accompanied the episodes with large adjustments in price levels. In addition to the high volatility during the global financial crisis, commodity markets also saw high volatility in the late 40s/early 50s and again around the oil price hikes in the early seventies.

Table 1 reports descriptive statistics for the commodity spot price changes. For comparison, we also use returns data on a stock market portfolio (based on the value-weighted CRSP index) and on the 10-year Treasury bond. To facilitate our subsequent analysis of monthly, quarterly, and annual price movements, we present statistics for all three frequencies. All commodity indexes earned positive nominal mean returns over the period, ranging from 0.18% per month for textiles to 0.43% per month for metals. These values are dominated by the mean returns on both stocks and T-bonds, however, at 0.98% and 0.48%, respectively.

Volatility varied a great deal across commodities, being lowest for industrials (2.84% per month) which was less than half the level observed for fat and oils (6.61%). All commodity returns were more volatile than the bond returns, while three indexes (fat and oils, livestock, and metals) were more volatile than the stock return series. Interestingly, while stock returns are left-skewed, all but one of the commodity series (metals) are right-skewed, suggesting that large increases in commodity prices are more common than large declines. Moreover, the kurtosis of commodity returns, a measure frequently used to gauge how "fat-tailed" returns are, exceeds that of both stock and bond returns.

While stock and bond returns are not serially correlated, three of the commodity spot return series (industrials, metals, and the broad index) are quite persistent with a first order autocorrelation around 0.3 at the monthly horizon. This serial correlation is only mildly reduced at the quarterly horizon, but disappears in the annual data. Since trades in spot markets can be associated with storage costs and risk premia may also be time-varying, serial correlation in spot market returns is clearly not proof of arbitrage opportunities.[5] Deaton and Laroque (1992, 1996) consider a model where speculators' trades induce serial correlation in commodity price levels, although they also find that speculation cannot explain the observed degree of serial correlation in commodity prices.

An analysis of cross-correlations among commodity returns shows that fats and oils, foods, and livestock prices are strongly correlated, while in turn industrials and metals are also strongly correlated. Textile prices tend to have the weakest correlation with other commodity price indexes.

3 Empirical results

Following studies on stock return predictability such as Goyal and Welch (2008), Campbell and Thompson (2008), and Rapach, Strauss and Zhou (2010), we first consider simple univariate prediction models of commodity price changes. These have the advantage of revealing the marginal predictive power of individual predictor variables.

We specify the univariate return regressions as follows:

$$r_{t+1:t+h} \equiv \frac{P_{t+h} - P_t}{P_t} = \beta_{0h} + \beta_{1h} x_t + \varepsilon_{t+1:t+h}, \tag{4}$$

where $r_{t+1:t+h}$ is the cumulated return between the end of period t and the end of period $t+h$, h is the horizon (equal to one, three, and twelve, for the monthly, quarterly, and annual regressions, respectively), and x_t is the lagged predictor variable.

3.1 In-sample return predictability

Pairing each of the commodity price series with each of the individual predictor variables, Table 2 reports in-sample estimates of slope coefficients obtained from equation (4). Panel A reports results for the monthly regressions, while Panels B and C show results for the corresponding quarterly and annual regressions. At the monthly horizon, variables such as the dividend-price ratio and the T-bill rate, which have been identified as predictors of stock and bond returns, fail to be significant for commodity price changes. Conversely, the long term return (ltr) has a negative and significant coefficient for the industrials, metals and broad commodity price index, while this variable generates positive slopes for stock and bond returns. This is similar to the observation by Hong and Yogo (2011) that the yield spread has the opposite sign for stocks and commodity futures returns. Exposure to this variable through a long position in stocks or bonds can therefore be partially hedged by simultaneously taking a long positions in commodities. The coefficient of

[5] We also examined serial correlation in a range of futures indexes and found, as expected, that such serial correlation is absent in the corresponding futures returns.

the default return spread (dfr) is positive and significant for industrials, livestock, and metals, but is insignificant for stocks and the other commodity indexes.[6]

Turning to the macroeconomic state variables, growth in industrial production and growth in the money supply are positively and significantly linked to the subsequent month's price changes in industrials, metals, textiles, and the broad commodity index. In contrast, changes in the unemployment rate are negatively correlated with subsequent metals and industrials price changes. These findings suggest that evidence of increased economic activity are positively correlated with subsequent commodity spot price movements. Unsurprisingly, given the earlier findings of a strong autoregressive component in many of the indexes, the lagged return is significant for most of the commodity price series, though not for stocks.

The evidence on predictability of commodity price movements varies substantially across different horizons. For example, whereas the inflation rate turned out to be insignificant for all commodity price indexes at the monthly horizon, in sharp contrast, at the quarterly horizon this predictor is significant at the 5% level for fats and oils, industrials, livestock, and the broad index, and it is significant at the 10% level for metals. In all cases the slope coefficient is negative. In contrast, the slope coefficients on the growth in money supply, $\Delta M1$, continue to be positive and highly significant for all commodity indexes except for fats and oils, and foods.

Predictability of commodity returns is strongest at the annual horizon, particularly for industrials, metals, and the broad commodity index for which the majority of predictor variables turn out to be significant. Macroeconomic state variables such as inflation, growth in industrial production, growth in the money supply and changes in the unemployment rate generate significant slope coefficients at the annual horizon for these indexes. In contrast, the lagged return is no longer significant at the annual horizon.

We conclude from these results that return predictability varies a great deal across different horizons. Variables such as the inflation rate are insignificant at the monthly horizon but become

[6]To evaluate statistical significance, we compute bootstrapped $p-$values repeating the following procedure 5,000 times: (i) resample T pairs of $(\hat{\varepsilon}, \hat{\eta})$, with replacement, from OLS residuals in regressions $r_{t+1} = \alpha + \varepsilon_{t+1}$ and $x_{t+1} = \mu + \rho x_t + \eta_{t+1}$; (ii) build up time series of predictors, x_t, from the unconditional mean $\hat{\mu}/(1-\hat{\rho})$ and iterate forward on the x_{t+1} equation using the OLS estimates $\hat{\mu}, \hat{\rho}$ and the resampled values of $\hat{\eta}_{t+1}$; (iii) construct time series of returns, r_t, by adding the resampled values of $\hat{\varepsilon}_{t+1}$ to the sample mean (under the null that returns are not predictable); (iv) use the resulting series x_t and r_t to estimate return regressions by OLS; (v) leave out the last $T-N+1$ observations to produce out-of-sample forecasts. The boostrapped p-values associated with the reported βs is the relative frequency with which the (absolute value) of the bootstrapped t-statistics in point (iv) exceed the actual value. The boostrapped p-values associated with the out-of-sample R^2 is the relative frequency with which the bootstrapped values in point (v) exceed the value recorded in the actual data.

significant at the quarterly and annual horizons, whereas growth in industrial production is significant in the monthly and annual regressions, but not in the quarterly ones. Only growth in the money supply seems capable of predicting commodity returns across all three horizons. Return predictability is also stronger for industrials and metals and weakest for fats-oils, foods, and textiles.

3.2 Out-of-sample return predictability

Measures of in-sample return predictability such as those reported in Table 2 are not true ex-ante measures of expected returns since they reflect data from the full sample which of course would not have been available to investors in real time. To address this issue, it is common to report out-of-sample predictability measures using recursively estimated parameter values to generate forecasts. For example, setting $z_t = (1\ x_t)'$ and using data from $\tau = 1, ..., t$, least squares parameter estimates $\hat{\beta}_t = (\sum_{\tau=1}^{t} z_{\tau-1} z'_{\tau-1})^{-1} (\sum_{\tau=1}^{t} z_{\tau-1} r_{\tau})$ can be obtained at time t and used to generate a forecast of r_{t+1}, $\hat{r}_{t+1|t} = \hat{\beta}'_t z_t$. The following period, $t+1$, data from $\tau = 1, ..., t+1$ can be used to obtain an estimate, $\hat{\beta}_{t+1} = (\sum_{\tau=1}^{t+1} z_{\tau-1} z'_{\tau-1})^{-1} (\sum_{\tau=1}^{t+1} z_{\tau-1} r_{\tau})$, generate a forecast, $\hat{r}_{t+2|t+1} = \hat{\beta}'_{t+1} z_{t+1}$, and so forth. This procedure continues until the end of the sample and ensures that look-ahead bias is absent from the coefficient estimates used to compute the forecasts. In our analysis we reserve data up to 1990:12 to estimate the model parameters and use the remaining 20 years of data, 1991:01-2010:12, for out-of-sample forecast evaluation.

For each of the univariate models Table 3 reports the out-of-sample R^2-value, measured relative to the value obtained from the benchmark model that only includes a constant and so sets $\beta_{1h} = 0$ in equation (4):

$$R^2 = 1 - \frac{\sum_{t=R}^{T-1} (r_{t+1} - \hat{r}_{t+1|t})^2}{\sum_{t=R}^{T-1} (r_{t+1} - \hat{r}_{t+1|t}^{bmk})^2}, \tag{5}$$

where $R = 1990m12$, and $T = 2010m12$. First consider the monthly results in Panel A. Many R^2-values are negative as a result of the effect of parameter estimation error which reduces the precision of the forecast, see, e.g., the discussion in Clark and West (2007) and Inou and Kilian (2008). However, for some of the predictor variables—notably, the T-bill rate, the term spread, the default return spread, inflation, growth in industrial production, and money supply growth—we find positive out-of-sample R^2-values for three or more of the commodity price series. Excluding lagged returns, the highest values, 4.3% and 4.5%, are obtained for the industrial raw materials and metals returns when the default return spread is used as the predictor. Once again, predictability appears strongest for industrials, metals, and the broad commodity price index, and notably weaker for fats-oils, foods, and livestock.

Overall, however, the single best predictor variable is the one-month lagged return which generates out-of-sample R^2-values of 5.2% (commodity price index), 7.2% (metals), and 9.1% (industrials). Interestingly, this predictor also generates a large negative R^2-value for textiles (-7.3%).

We evaluate the statistical significance of the out-of-sample predictability results using the test statistic proposed by Clark and West (2007). This test statistic measures the difference between the out-of-sample MSE-value of a given forecast versus that of the benchmark constant return model, but corrects for the higher variability of the forecasts from the univariate models that include an additional predictor variable by basing inference on the adjusted mean-squared error:

$$\Delta MSE^{adj} = P^{-1}\sum_{t=R}^{T-1}\bar{e}^2_{t+1|t} - P^{-1}\sum_{t=R}^{T-1}\hat{e}^2_{t+1|t} + P^{-1}\sum_{t=R}^{T-1}(\bar{r}_{t+1|t} - \hat{r}_{t+1|t})^2. \tag{6}$$

Here $\bar{e}^2_{t+1|t}$ is the squared forecast error from the prevailing mean model, $\hat{e}^2_{t+1|t}$ is the squared forecast error from the univariate forecasting model, while $\bar{r}_{t+1|t}$ is the prevailing mean forecast and $\hat{r}_{t+1|t}$ is the forecast from the univariate model that nests the prevailing mean model. $P = T - R$ is the size of the forecast evaluation sample. Positive values of this measure suggest that the benchmark is associated with larger forecast errors and so the univariate prediction model dominates. Notice that the final term in (6) corrects for the typically higher variability associated with the forecasts generated by the larger (univariate) model, relative to the prevailing mean forecast.

The results are very much in line with the out-of-sample R^2-values and show that the forecasts based on the T-bill rate, the default return spread, and money supply growth are significant at the 10% level (or less) for the industrials and metals commodity price indexes. Finally, the forecasts based on the lagged return generate highly significant, positive R^2-values for industrials, metals, and the broad commodity price index.

At the quarterly horizon (Panel B), out-of-sample return predictability grows stronger. In fact, for the univariate models based on the T-bill rate, inflation, and the money supply growth we find positive, and in many cases statistically significant R^2-values, for the majority of the commodity series. Note that predictor variables such as the inflation rate work far better at the quarterly than at the monthly horizon, so, once again, it is not clear that the best prediction model is identical across different horizons.

The tendency for the return predictability results to strengthen when going from the monthly to the quarterly regressions carries over to the annual results where out-of-sample R^2-values in the range 10-20% are found for the models based on the T-bill rate or the term spread and the macroeconomic predictors (growth in industrial production, money supply growth, and changes in the unemployment rate). In sharp contrast with the earlier results, the lagged return does not generate positive out-of-sample R^2-values at the annual horizon.

Conversely, some of the R^2-values become more negative at the quarterly and, particularly, annual horizons. This is to be expected: our forecasts are based on non-overlapping observations which means that there are far fewer data points on which to estimate the annual models than the monthly models. In turn this results in larger estimation errors and so explains the large negative out-of-sample R^2-values.[7]

One way to inspect how return predictability evolves over time is by examining the cumulated sum of squared error differential between the benchmark model and a candidate prediction model proposed by Goyal and Welch (2008):

$$\Delta SSE_t = \sum_{\tau=1}^{t} e_\tau^2(Bmk) - \sum_{\tau=1}^{t} e_\tau^2(Model). \tag{7}$$

Positive values of this measure indicate that the candidate forecasting model has produced more accurate forecasts than the benchmark model up to that point in time. Periods associated with an increase in ΔSSE suggest that the particular forecasting model produced a lower MSE-value than the benchmark, while conversely declines in ΔSSE suggest that the forecasts were less precise than those based on the benchmark. Hence plots of ΔSSE provide a useful diagnostic that helps identify periods of (relative) out- or underperformance. Figure 3 provides such plots for the raw industrials (left windows) and metals (right windows) indexes based on the univariate return prediction model that uses money supply growth as the predictor variable. At the monthly and quarterly horizons, the forecasts underperform in the early sample up to around 1993, before steadily outperforming up to 2002. This is followed by a period of underperformance from 2005-2008, before superior performance returns between 2008 and 2010. Compared with the monthly and quarterly models, the superior performance of the annual forecasts against the prevailing mean model evolves more steadily, as can be seen from the two lower diagrams.[8]

Given the strong performance of the monthly, quarterly, and annual forecasts based on the simple AR(1) model, it is natural to ask if any of the financial and macroeconomic predictor variables help improve the precision of the forecasts, over and above the lagged return. To address this point, we consider a bivariate regression model that includes the lagged return and a single predictor variable:

$$r_{t+1:t+h} = \beta_{0h} + \beta_{1h} r_{t-h+1:t} + \beta_{2h} x_t + \varepsilon_{t+1:t+h}. \tag{8}$$

[7]Note that this is not just an issue for the commodity return predictions but also hold for the stock return forecasts for which every single out-of-sample R^2-value is negative at the annual horizon.

[8]Further inspection of the out-of-sample forecasts for the monthly and quarterly models suggest that the ability of individual predictor variables to improve on the forecasts from the simple constant return model is not particularly stable over time. The predictor variables that are best able to generate stable outperformance over the benchmark is the T-bill rate, the default return spread (dfr) and money supply growth.

The benchmark model is now the AR(1) specification which is obtained by setting $\beta_{2h} = 0$ in equation (8). Table 4 shows the marginal R^2-values, i.e., the change in the out-of-sample R^2 of the forecasting model in equation (8) compared with the AR(1) specification. At the monthly horizon the results reveal little evidence that any predictor adds to the predictive performance of the AR(1) model. At the quarterly horizon, the inflation rate in particular, but also the investment-capital ratio and money supply growth help significantly improve on the AR(1) forecast of returns on the industrials and metals indexes. At the annual horizon, the results are largely unchanged relative to the model that used the simpler prevailing mean specification as the benchmark, and most predictor variables add value over the AR(1) benchmark, particularly for industrials, metals, and the broad commodity index.

3.3 Forecasts of Levels of Commodity Prices

So far we have focused on modeling percentage changes (i.e., returns) on the commodity price indexes. An alternative is to directly predict the price level as a function of its past value and the same list of predictors considered thus far. Although statistical tests suggest that there is a unit root in all of the commodity price indexes, this procedure is still of interest given that it allows us to relax this assumption. Table 5 reports out-of-sample R^2-values for this exercise, computed in percentage terms for comparison with Table 3. The reuslts are quite comparable to those in Table 3. At the monthly horizon, there is only modest evidence of predictability with the default rate and growth in industrial production producing significant results for the industrials, metals and broad commodity indexes. Inflation works well as a predictor at the quarterly horizon, while a broader set of macroeconomic variables in addition to the term spread generate significant R^2-values at the annual horizon.

3.4 Forecasting performance in recessions and expansions

Studies such as Rapach, Strauss and Zhou (2010) and Henkel, Martin, and Nardari (2011) find that predictability of stock returns is stronger during slow growth or recessionary states of the economy. Since many of our predictor variables, particularly the macroeconomic ones, are related to the economic cycle, we next explore if there is state-dependence in the strength of the predictive evidence. To this end, Table 6 compares the out-of-sample R^2-values in recessions, as defined by the NBER, versus expansions. Specifically, we evaluate the statistical significance of differences in predictive power in recessions relative to expansions using regressions of the squared error return difference

$$(r_{t+1:t+h} - \bar{r}_{t+1:t+h|t})^2 - (r_{t+1:t+h} - \hat{r}_{t+1:t+h|t})^2 = \alpha + \beta NBER_{t+1} + \varepsilon_{t+1:t+h}, \tag{9}$$

where $(r_{t+1:t+h} - \bar{r}_{t+1:t+h|t})^2$ is the squared forecast error of the constant (prevailing mean) benchmark, $(r_{t+1:t+h} - \hat{r}_{t+1:t+h|t})^2$ is the squared forecast error for the univariate prediction model, and $NBER_{t+1}$ is a recession indicator which is unity during recessions and zero during expansions. Positive and significant values of β suggest that the univariate prediction model is more accurate, relative to the benchmark, during recessions than during expansions. Note that by considering forecasting performance relative to the benchmark, we control for the fact that commodity price volatility may be higher during recessions than during expansions.

Table 6 shows that there is little evidence of commodity price predictability during expansions. In contrast, predictability is significantly stronger during recessions. The strongest evidence to this effect is found for the inflation rate. This variable shows no predictive power during expansions, but has strong predictive power−with out-of-sample R^2-values up to 3.2% for industrials at the monthly frequency and an R^2-value above 10% for most of the commodity indexes at the quarterly frequency. Similarly, industrial production growth, and growth in money supply show evidence of having significantly stronger predictive power during recessions than during expansions, as does the lagged return.

These findings suggest that predictability of commodity prices is highly state dependent. For example, inflation *does* predict commodity prices, but only in recession states. This suggests perhaps the need for developing models that account for such dependencies, one example being the regime switching models recently reviewed by Ang and Timmermann (2011).

4 Multivariate Regressions

So far we have analyzed the effect of individual predictor variables. It is natural, however, to inquire what happens if multivariate information is used. To this end we study three strategies. First, we use the Akaike (AIC) and Bayesian (BIC) information criteria to select which variables to include among the full set of predictor variables. These criteria trade off model parsimony against fit, with the BIC most heavily penalizing additional included variables. Again we implement the variable selection recursively, at each point in time considering all possible 2^N combinations of predictor variables.

Second, we consider shrinkage methods such as ridge regression and subset combinations which are designed to reduce the effect of parameter estimation error on the forecasts. Ridge regression requires selecting a parameter λ which regulates the amount of shrinkage imposed on the regression coefficients:

$$\hat{\beta}_{\lambda t} = \arg\min_{\lambda} \left(\sum_{\tau=1}^{t} (r_\tau - z'_{\tau-h}\beta_{\lambda t})^2 + \lambda \sum_{j=1}^{K} \beta_{\lambda tj}^2 \right). \tag{10}$$

Given a value of λ, and a vector of predictors $z_t = (1\ x_t')'$, the forecasts are obtained as

$$\hat{r}_{t+h|t}^{RIDGE} = z_t' \hat{\beta}_{\lambda t}. \tag{11}$$

By construction, as $\lambda \to \infty$, $\hat{r}_{t+h|t}^{RIDGE} \to \frac{1}{t-1}\sum_{j=2}^{t} r_j$, so the ridge forecast simply converges to the sample mean. Following Inoue and Kilian (2008), we consider a range of shrinkage values $\lambda \in \{0.5, 1, 2, 3, 4, 5, 10, 20, 50, 100, 150, 200\}$.

The subset regression approach, recently introduced by Elliott, Gargano, and Timmermann (2012), uses equal-weighted combinations of forecasts based on all possible models that include a particular subset of the predictor variables. Suppose the set of potential predictor variables includes K different predictors. In our case $K = 11$ or $K = 12$ depending on the horizon. Each subset is defined by the set of regression models that includes a fixed (given) number of regressors, $k \leq K$. Specifically, we run the 'short' regression of r_{t+1} on a particular subset of the regressors, then average the results across all $k \leq K$ dimensional subsets of the regressors to provide an estimator, $\hat{\beta}$, for forecasting. With K regressors in the full model and k regressors chosen for each of the short models there are $K!/(k!(K-k)!)$ subset regressions to average over. For example, the univariate case ($k = 1$) has K such short regressions, each with a single variable. The equal-weighted combination of the forecasts from the individual models is then

$$\hat{r}_{t+1|t} = \frac{1}{K} \sum_{i=1}^{K} x_{ti}' \hat{\beta}_{it}. \tag{12}$$

This strategy was used by Rapach, Strauss and Zhou (2010).

4.1 Empirical Results

First consider the information criteria. Since we apply these criteria recursively, they provide interesting insights into which variables get selected at different points in time. For each of the three frequencies, Figure 4 uses the raw industrials index to present this information for the variables under consideration. At each point in time this graph shows which variables get selected by the AIC (left windows) or BIC (right windows) to predict spot returns.

At the monthly frequency the lagged return, money supply growth, industrial production growth, and the T-bill rate get included by the AIC in almost all periods, whereas the inflation rate, long-term return, and the default return spread get included at certain contiguous blocks of time. In contrast the unemployment rate, commodity volatility, the term spread and the dividend-price ratio never or rarely get selected. The BIC is known to penalize inclusion of additional parameters more heavily than the AIC and so only includes industrial production and lagged returns throughout the sample, whereas money supply growth gets included towards the end of the sample.

At the quarterly frequency, the AIC includes almost all variables all of the time except for the investment-capital ratio and the dividend yield, which never get selected, and the unemployment rate which rarely gets selected. Similarly, the BIC also includes more variables than at the monthly frequency, with the lagged return, long term returns, industrial production, the T-bill rate, and money supply growth featuring prominently. The quarterly BIC results suggest that the preferred model does not remain invariant through time, with industrial production and long term returns getting selected up to 1998, and money supply growth and the T-bill rate selected most periods after 2001.

At the annual frequency, both the AIC and BIC select the unemployment rate, money supply growth and inflation as predictors most periods. In addition, the AIC selects the term spread and commodity volatility during the last three years of the sample.

Figure 5 shows results for the metals price index. While there are many similarities with the results for the raw industrials index, there are also important differences. For example, the long term return now gets selected by the BIC while the commodity volatility gets selected by the AIC at the monthly frequency. At the quarterly horizon, the lagged return gets selected less frequently for metals than it did for raw industrials, while industrial production growth remains important in the models selected by BIC. At the annual frequency the AIC chooses more predictors for metals than it did for raw industrials, and the models selected by the BIC are less stable with both the T-bill rate and commodity price volatility now getting selected in some periods.

Table 7 reports the out-of-sample forecasting performance of the models selected by the AIC or the BIC. For industrials, metals, and the broad commodity index, the monthly out-of-sample R^2-values, reported in Panel A1, are positive and lie in the range 5-11%. Small, positive R^2-values are also obtained for foods and livestock under the models selected by AIC. For the other cases, most notably fats-oils and textiles, negative R^2-values are obtained. At the quarterly frequency (Panel B1), only the AIC manages to generate positive R^2-values for industrials, metals and broad commodity returns. In contrast, at the annual frequency (Panel C1) both the AIC and the BIC produce positive and, in some cases, very large R^2-values.

Figure 7 plots the annual out-of-sample forecasts of raw industrials and metals returns generated by the complete subset regressions over the period 1991-2010. Each line corresponds to a different value, k, tracking the number of included variables in the prediction model. The fewer variables get included in the models, the smoother the averaged forecast tends to be. The figure illustrates that although the forecasting models clearly missed the magnitude of the decline in commodity prices in 2008, they did a better job at predicting the subsequent bounceback in 2009 and 2010.

The predictive performance of the ridge and subset regressions is reported in Table 7. At the monthly frequency, the ridge regressions generate positive out-of-sample R^2-values around 10% (industrials), 8% (metals) and 4-5% (broad index), and small, positive R^2-values for livestock returns. In contrast, negative R^2-values are obtained for fats-oils, foods, and textiles. Results are very similar for the subset regressions that include a suitable number of predictor variables. At the quarterly frequency, similar results are obtained, although R^2-values tend to be somewhat higher than at the monthly horizon for industrials, metals and the broad commodity index. Performance is further boosted at the annual frequency, where out-of-sample R^2-values in the range 20-35% is seen for the broad commodity index and some of the disaggregate indexes. Notice the contrast to the negative out-of-sample R^2-values for the annual stock return predictions.

The simple equal-weighted average of all possible univariate forecasts is shown as the first line ($k = 1$) under the subset regressions. Rapach, Strauss, and Zhou (2010) found that this method provided good out-of-sample forecasts for stock returns. At the monthly horizon the out-of-sample R^2 for metals and industrials is around 3% under this approach. This rises to around 4% for industrials at the quarterly horizon and grows further to 10% for industrials and 6% for metals at the annual horizon. In fact this strategy is dominated by combining forecasts from models with many more predictor variables. Including on the order of 5-8 predictor variables can in many cases double or triple the value of the out-of-sample R^2 compared with the equal-weighted combination of univariate forecasts. This is related to the fact that the best models include relatively many predictors.

5 Forecasting commodity price volatility, increases, and decreases

Our analysis has so far focused on predictability in the mean of commodity returns. However, it is clearly of interest to explore whether the volatility of commodity returns is predictable through time and to what extent such predictability might vary with the state of the economy. While we are unaware of studies that have addressed this question for commodity prices, a large literature has found that stock market volatility follows a pronounced counter-cyclical pattern (Schwert (1989)). Interestingly, there is relatively weak evidence that macroeconomic state variables contain information useful for predicting stock market volatility. Engle, Ghysels and Sohn (2007) find some evidence that inflation volatility helps predict the volatility of stock returns. However, the volatility of interest rate spreads and growth in industrial production, GDP or the monetary base fail to consistently predict future volatility, with evidence being particularly weak in the post-WWII sample. This is consistent with findings in Paye (2010) and Ghysels, Santa-Clara and Valkanov (2006).

Figure 7 shows a plot of the logarithm of the realized commodity volatility series constructed using equation (3). The series displays low frequency movements, trending downwards from 1947 until 1963, before increasing up to the late seventies, slowly drifting down until the early nineties, and then trending up until the end of the sample.

Following Paye (2010) and others, we model the logarithm of the realized commodity variance (i.e., the square of the realized commodity volatility measure in (3)) as the basis for our analysis. Realized commodity variance is highly skewed and fat-tailed, whereas the logged value is much closer to normality. This makes inference easier and dampens the impact of outliers. Unsurprisingly, data analysis confirmed that commodity volatility (or its logged value) is highly persistent, so we include a first-order autoregressive component in our models. Specifically, we explore forecasting models of the form

$$\log(cvol_{t+1}^2) = \beta_0 + \beta_1 \log(cvol_t^2) + \beta_2 x_t + u_{t+1}. \tag{13}$$

Table 8 presents empirical results from estimating (13). The estimate of β_1 in the univariate regression is close to 0.8 at all three horizons and highly significant, which is in line with work on stock return volatility. β_2 tracks the predictive content of the state variables after controlling for serial correlation in commodity volatility. The coefficients of the dividend-price ratio and term spread are significant at both the monthly and quarterly frequencies, while the inflation rate and growth in money supply are significant at the monthly frequency and the investment-capital ratio is significant at the quarterly frequency.

Turning to the out-of-sample predictive performance, we report the incremental change in the out-of-sample R^2-value, relative to that from an AR(1) model obtained by setting $\beta_2 = 0$ in equation (13). The evidence is very weak when it comes to establishing that the economic covariates improves upon the predictive power of the AR(1) model. In fact, only the term spread variable at the monthly horizon and the default return spread at the annual horizon seems able to marginally improve on the AR(1) model. This is consistent with earlier findings for stock market volatility such as those reported by Paye (2010).

Although few, if any, state variables appear capable of improving upon the out-of-sample predictive accuracy of the AR(1) model for (log-) commodity volatility, the story is quite different when it comes to separately assessing the predictive performance in expansions versus recessions, as judged by the NBER recession indicator. The last two columns in Table 8 show that during economic recessions several variables, most notably the macroeconomic variables (growth in industrial production, money supply growth, and changes in the unemployment rate), produce better out-of-sample forecasts of monthly commodity market volatility when added to the AR(1) model. The evidence is weaker at the quarterly and annual horizons, although at the quarterly horizon the inflation rate produces notably better out-of-sample forecasts of commodity market volatility in recessions when added to the AR(1) model.

5.1 Predictability of commodity price increases and decreases

Hamilton (2003, 2011) suggests that large increases in oil prices can have a particularly negative effect on economic growth. Specifically, he proposes using $\max(0, p_t - \max(p_{t-1}, ..., p_{t-12}))$, where p_t is the oil price, as a predictor of economic growth. Given the interest in predicting increases in oil prices, we next explore whether increases in commodity prices more broadly defined can be predicted. We initially simplify the analysis and consider monthly price increases, defined as $\max(0, r_{t+1:t+h})$.

First note that if $X \sim N(\mu, \sigma^2)$, from the moments of a truncated normal distribution, we have

$$\begin{aligned} E[\max(0,X)] &= E[\max(0,X)|X \geq 0]p(X \geq 0) \\ &= E[X|X \geq 0]p(X \geq 0) \\ &= E[X|X \geq 0]\left(1 - \Phi(\frac{-\mu}{\sigma})\right) \\ &= \left(\mu + \frac{\sigma\phi(-\mu/\sigma)}{1-\Phi(-\mu/\sigma)}\right)\left(1 - \Phi(\frac{-\mu}{\sigma})\right) \\ &= \mu\left(1 - \Phi(\frac{-\mu}{\sigma})\right) + \sigma\phi(\frac{-\mu}{\sigma}). \end{aligned} \tag{14}$$

Hence the expected value of $\max(0, X)$ depends on both the mean and the volatility of commodity returns. This suggests including both the lagged return and the lagged volatility in our benchmark model and then add the individual predictor variables:

$$\max(0, r_{t+1:t+h}) = \beta_{0h} + \beta_{1h} r_{t-h+1:t} + \beta_{2h}\sigma_{t-h+1:t} + \beta_{3h} x_t + \varepsilon_{t+1:t+h}. \tag{15}$$

Table 9 reports estimates from this regression applied to the monthly (panel A), quarterly (panel B), and annual (panel C) data. We show both full-sample slope estimates (based on the period 1947-2010) as well as out-of-sample R^2-values computed for the 20-year period 1991-2010. First consider the monthly coefficient estimates. Unsurprisingly, given (14), the lagged volatility is highly significant across all commodity indexes, as are lagged commodity returns. In addition, the inflation rate is positive and significant for foods and livestock, whereas money supply growth and industrial production are significant for three of the commodity indexes, including industrials and metals. For most other cases, the individual predictors are insignificant. The out-of-sample R^2-estimates show similar results with money supply growth notably continuing to help improve predictive accuracy for four of the commodity indexes.

At the quarterly frequency the lagged volatility continues to be highly significant in-sample, while the results for the AR(1) coefficient are somewhat weaker. Money supply growth and inflation continue to be significant, however, for raw industrials and metals. These results carry over to the out-of-sample R^2-values where money supply growth now improve the predictive accuracy by more than 2% for four of the commodity indexes.

Figure 8 plots the quarterly out-of-sample forecasts of $\max(0, r_{t+1})$ for the raw industrials and metals indexes using the prediction model that includes the lagged return, lagged volatility, and money supply growth as predictors. Clearly the forecasts are far from perfect, but they increased notably during the rebound in commodity prices that began in March 2009.

Finally, at the annual frequency, we find that both the coefficient estimates and out-of-sample R^2-values are significant for a broader range of the individual predictor variables$-$notably inflation, the investment-capital ratio and the change in the unemployment rate$-$although, in line with the earlier results, both lagged commodity volatility and lagged returns play far less of a role compared with the monthly and quarterly results.[9]

We also explore whether $\min(0, r_{t+1})$ is separately predictable by means of the same list of economic state variables. At the monthly frequency, the strongest evidence comes from growth in industrial production which appears capable of significantly increasing the out-of-sample R^2-value when added to the autoregressive and volatility terms for raw industrials, metals, and textiles. At the quarterly frequency, the results are very strong for the inflation rate which significantly raises the out-of-sample R^2-value for all commodity indexes, in some cases by more than 5%. This strong predictive performance from the inflation rate largely carries over to the annual frequency.

Comparing the results for $\max(0, r_{t+1})$ to those for $\min(0, r_{t+1})$, different state variables appear able to predict increasing versus decreasing commodity prices. Whereas money supply growth,

[9]We also considered predictability of the variable in Hamilton (2003), $\max(0, p_t - \max(p_{t-1}, ..., p_{t-12}))$. For four of the six commodity indexes we found that the inflation rate increased the out-of-sample R^2-value by about 1-2% when added to a lag and the conditional volatility. For the two remaining indexes, industrials and metals, growth in industrial production significantly increased the out-of-sample R^2-value.

lagged volatility, and the lagged return possess predictive power over increases in commodity prices, inflation and, to some extent, growth in industrial production, are far better predictors of declines in commodity prices.

6 Conclusion

Using spot price data on a sample of commodity indexes over the period 1947-2010, we examine the predictability of commodity spot price changes at the monthly, quarterly, and annual horizons. We establish out-of-sample return predictability by means of variables such as the default return spread, growth in money supply, and the T-bill rate. Some variables, such as the inflation rate, have little or no predictive power at the monthly horizon, but appear to have stronger predictive power over commodity spot price changes at the quarterly and annual horizons. At the annual horizon, a wide set of macroeconomic variables such as the growth in industrial production, money supply growth, and the change in the unemployment rate possess predictive power over returns. In addition, our results suggest that predictability of commodity spot price changes is stronger during economic recessions than during expansions and that different variables help predict commodity price increases versus decreases. This is important in light of research linking commodity price increases to economic recessions.

While a large literature has focused on establishing in-sample return predictability for futures and forward prices, our study is one of the first to empirically examine the behavior of the underlying spot prices in an out-of-sample context. Our results suggest that far from following a random walk, spot prices contain a sizeable predictive component which could prove helpful when pricing futures contracts.

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Figure 1: **Commodity prices.** This figure plots monthly values of the Reuters/Jeffries-CRB spot price indexes compiled by the Commodity Research Bureau. Prices are measured in nominal US dollar terms. The indexes are based on 22 individual commodities including raw industrials (burlap, copper scrap, cotton, hides, lead scrap, print cloth, rosin, rubber, steel scrap, tallow, tin, wool tops, and zinc) and foodstuffs (beans, butter, cocoa, corn, cottonseed oil, hogs, lard, steers, sugar, and wheat). The sample period is 1947-2010.

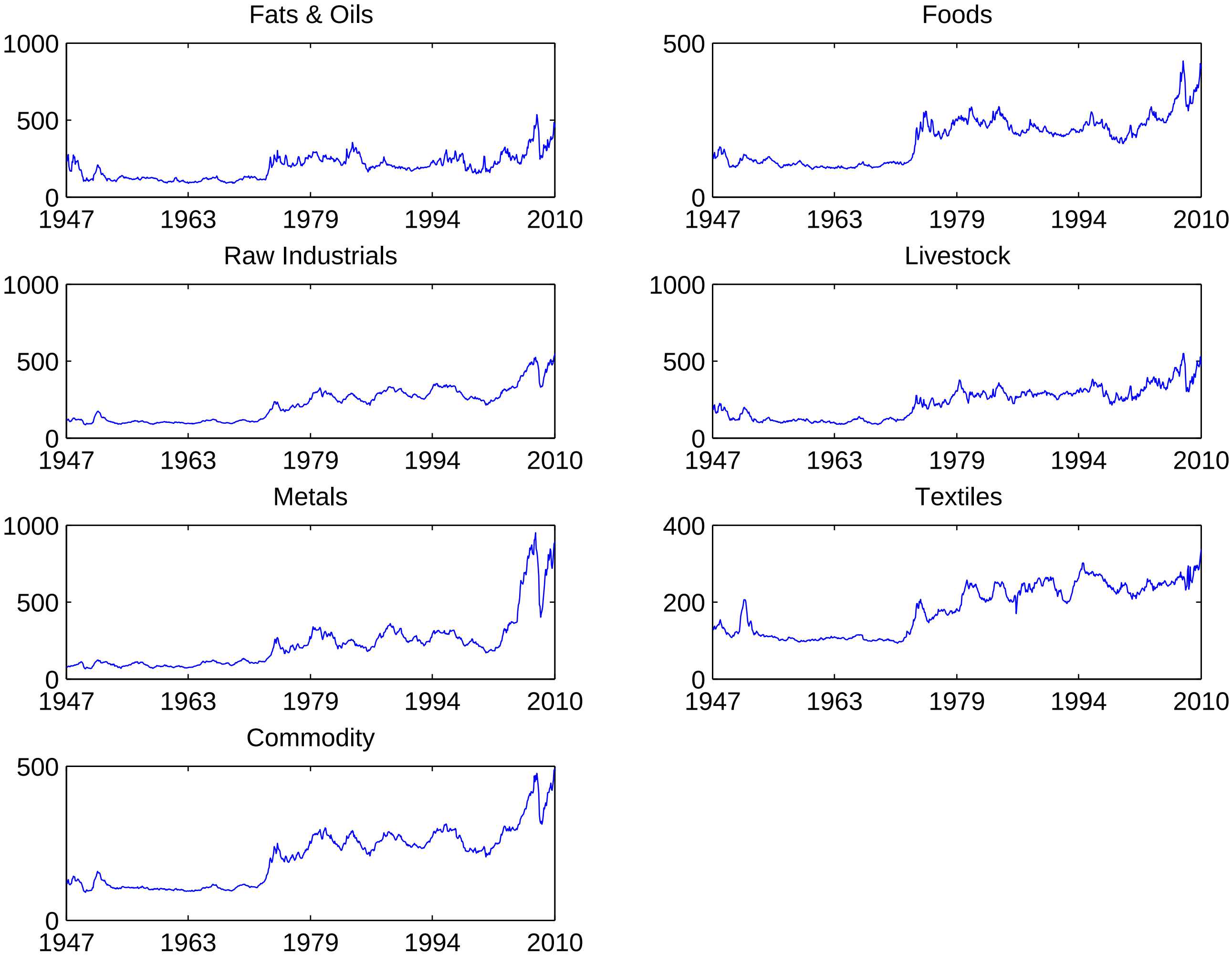


Figure 2: **Commodity returns.** This figure plots monthly returns on the Reuters/Jeffries-CRB spot price indexes compiled by the Commodity Research Bureau. Prices are measured in nominal US dollar terms.

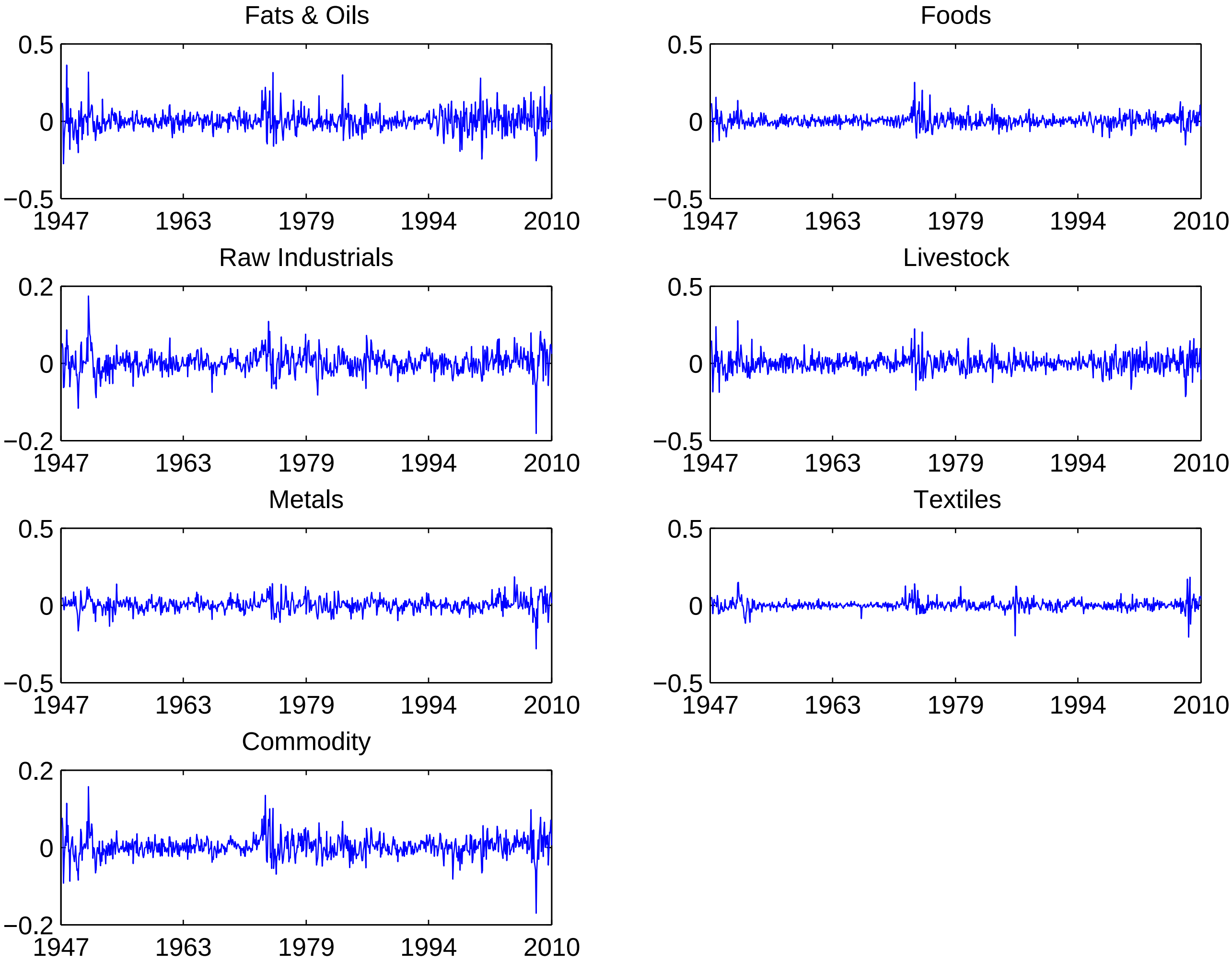


Figure 3: **Cumulated sum of squared forecast error differences.** The figures plot the sum of squared forecast error differences between the benchmark constant mean model and a prediction model that includes a constant and the lagged money supply as the predictor variable. Positive and rising values suggest that the time-varying predictor model outperforms the constant benchmark, while negative and declining values suggest the opposite. The top row uses monthly returns; the middle row uses quarterly returns, while the bottom row uses annual returns, all over the period 1991-2010. All forecasts are generated recursively, using an expanding window of data going back to 1947.

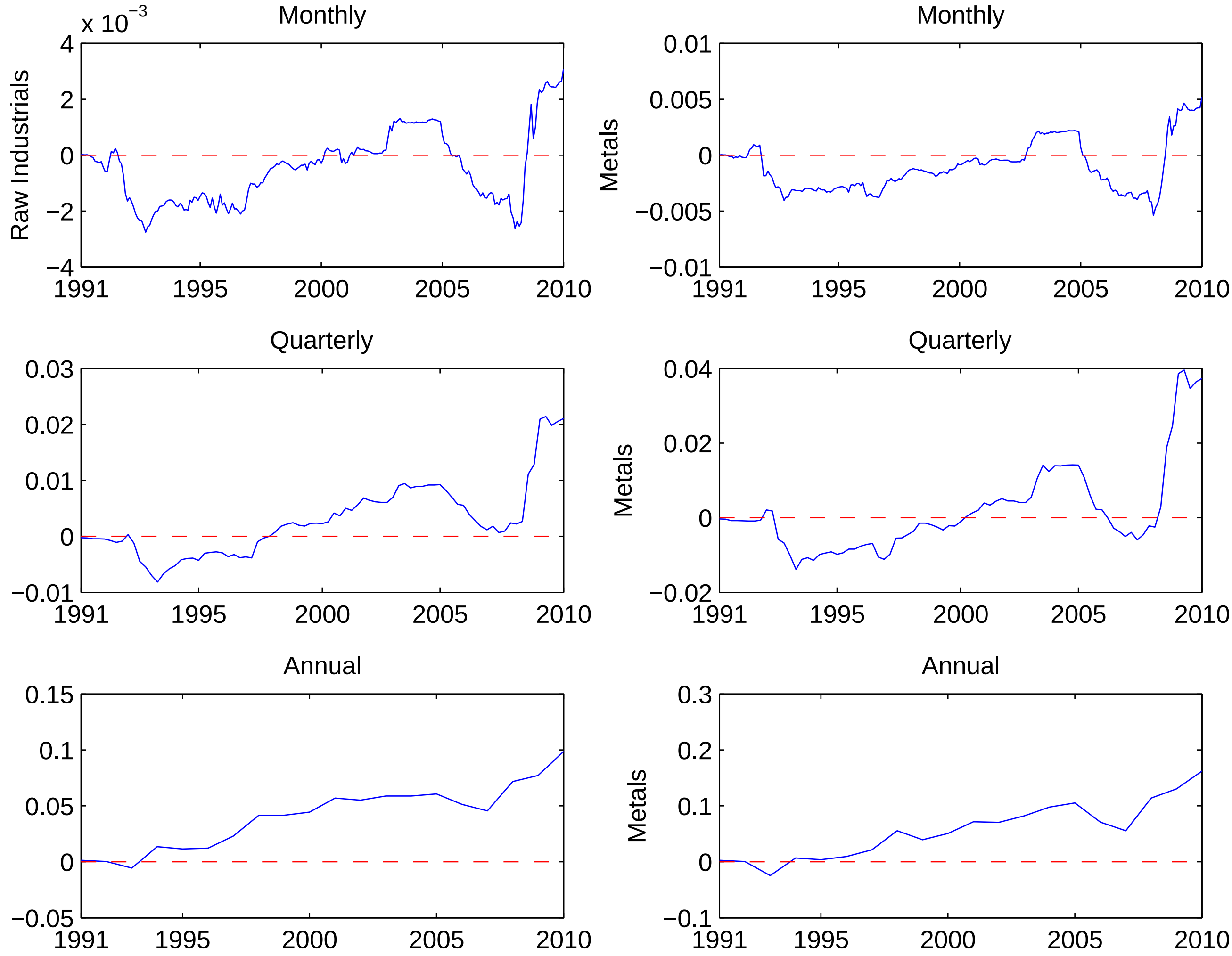


Figure 4: **Variable selection plots: Raw industrials index.** The plots mark which variables are selected at a given point in time by the Akaike (AIC) or Bayes (BIC) information criterion using asterisks to indicate inclusion. The dependent variable is the return on the raw industrials commodity price index, while the predictor variables are selected from the list indicated on the vertical axis. Estimation and variable selection is conducted recursively over the out-of-sample period 1991-2010. The top row uses monthly returns; the middle row uses quarterly returns, while the bottom row uses annual returns, all over the period 1991-2010.

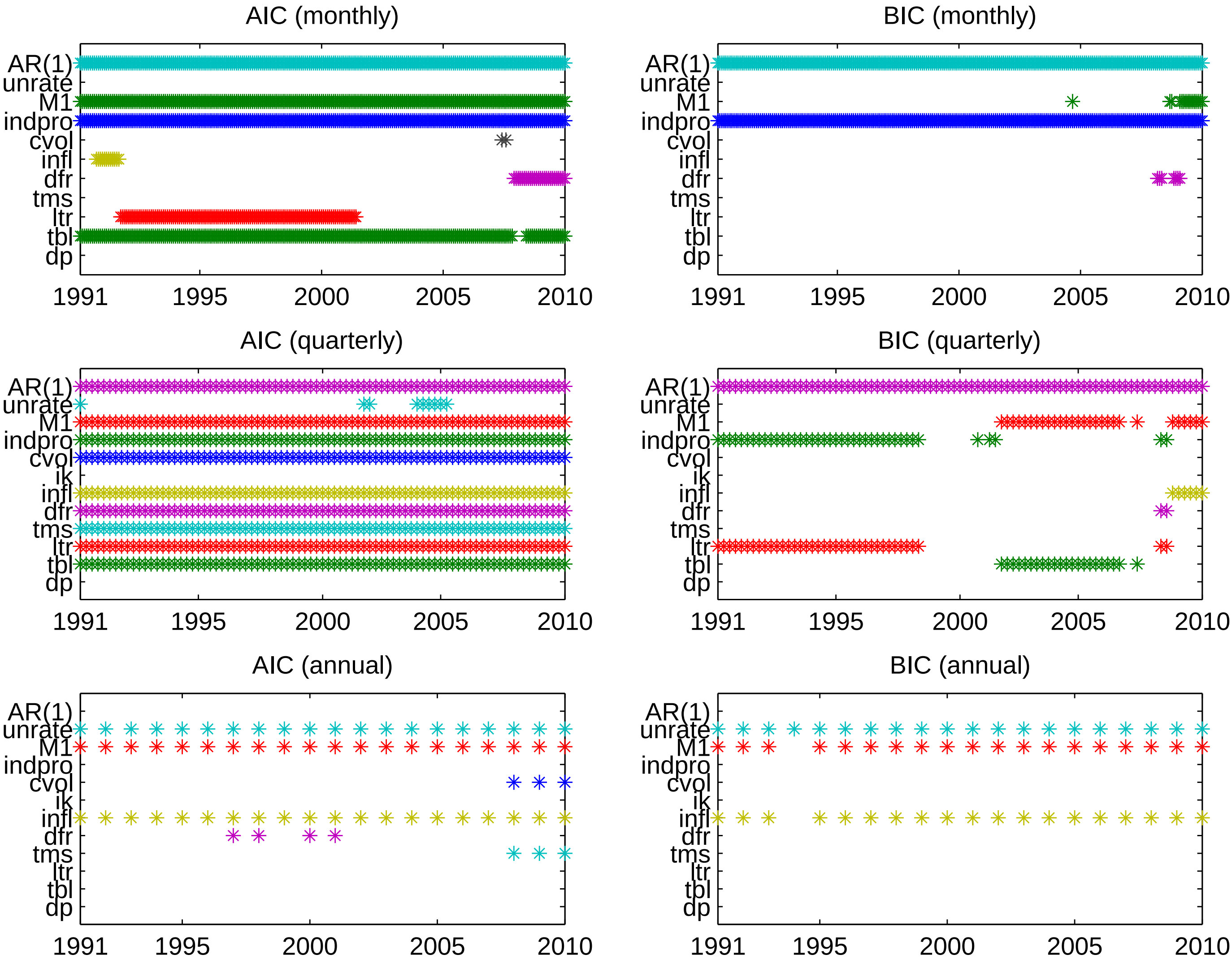


Figure 5: **Variable selection plots: Metals index.** The plots mark which variables are selected at a given point in time by the Akaike (AIC) or Bayes (BIC) information criterion using asterisks to indicate inclusion. The dependent variable is the return on the metals commodity price index, while the predictor variables are selected from the list indicated on the vertical axis. Estimation and variable selection is conducted recursively over the out-of-sample period 1991-2010. The top row uses monthly returns; the middle row uses quarterly returns, while the bottom row uses annual returns, all over the period 1991-2010.

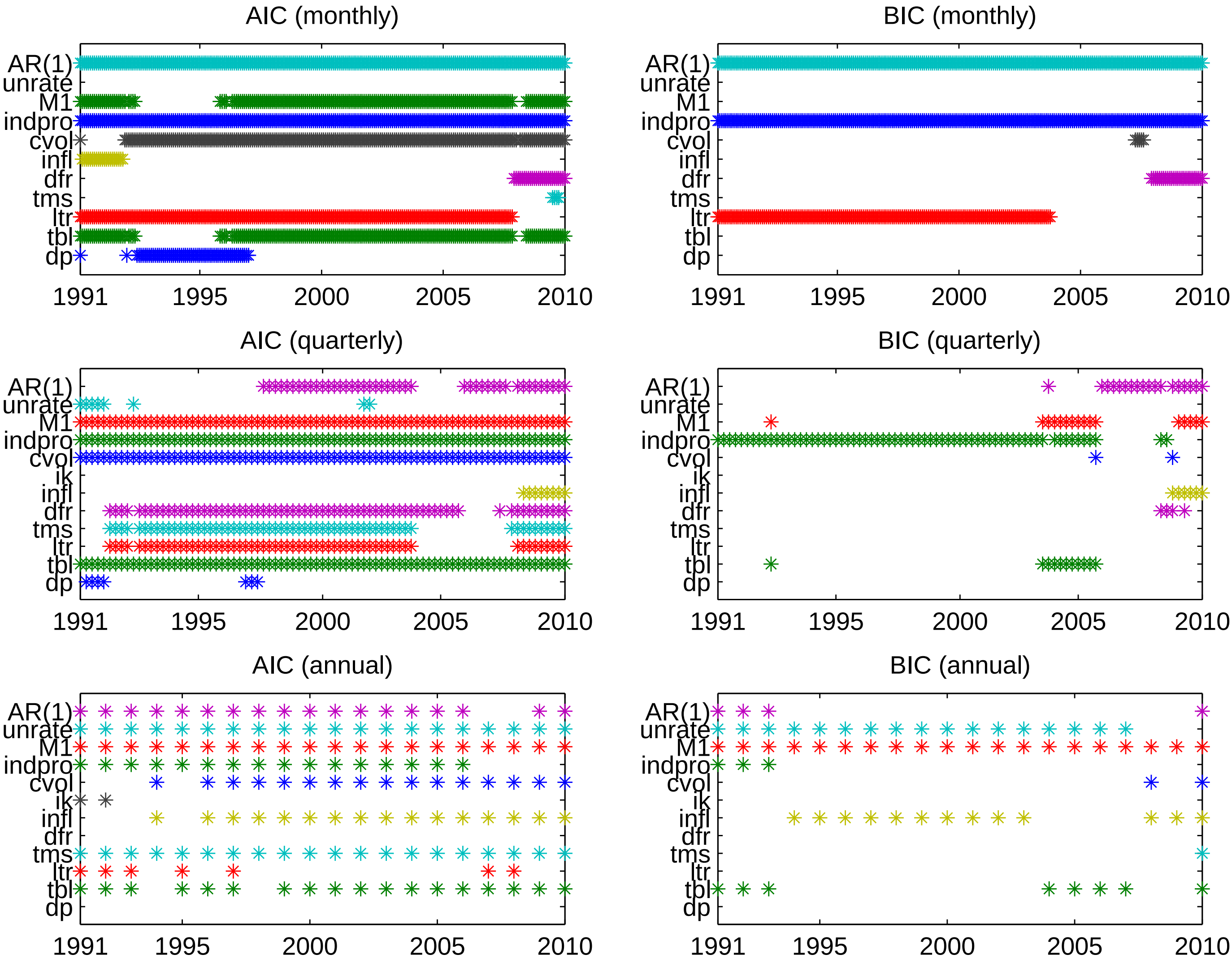
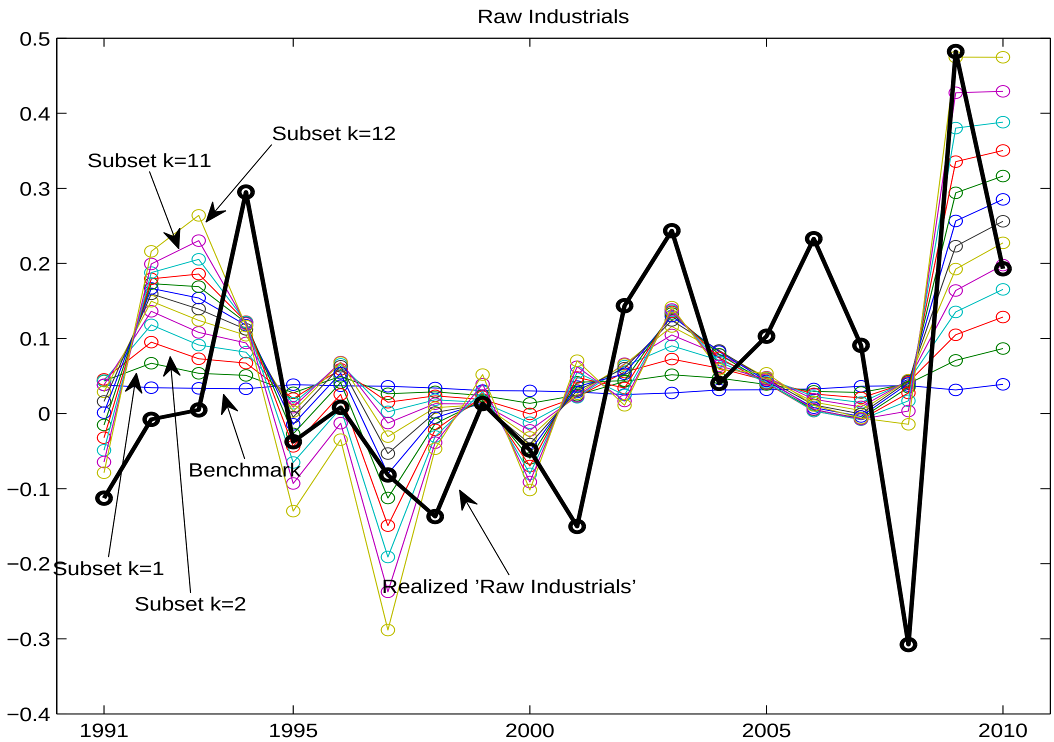


Figure 6: **Forecasts from complete subset regressions.** The figure plots the annual forecasts for the complete subset regressions that combine forecasts from all possible models with k=1, k=2,..., k= 12 predictor variables. The thick black line tracks the actual (realized) return on the corresponding commodity spot price index.



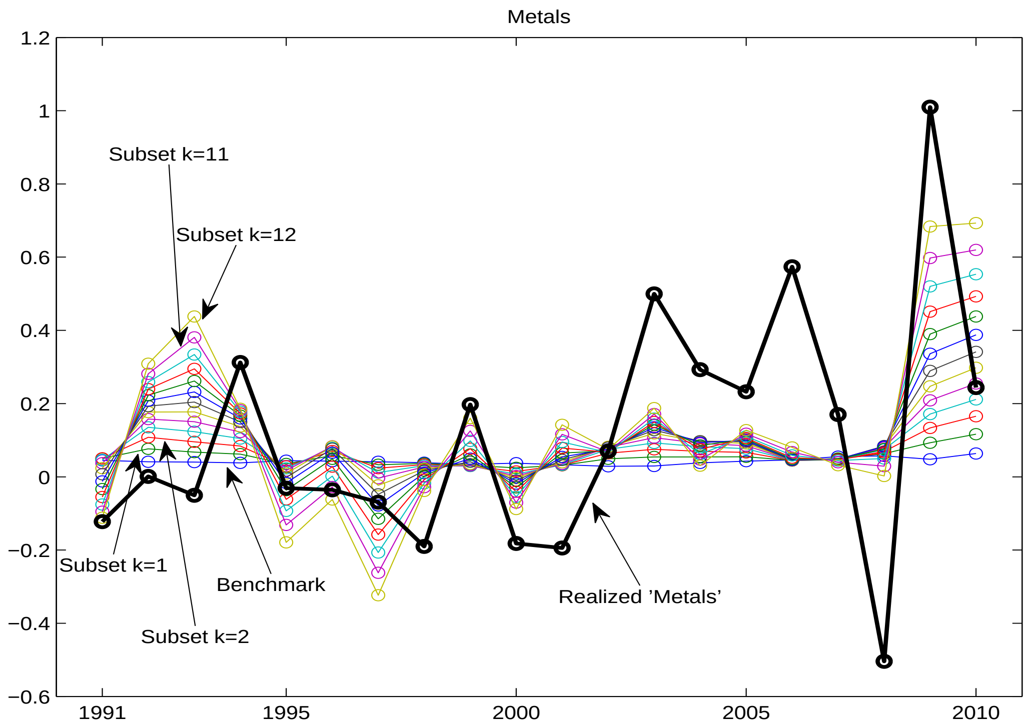


Figure 7: **Commodity variance.** This figure plots monthly values of the logarithm of the realized commodity price variance computed as the sum of squared daily returns of the Dow Jones-AIG Commodity Index over the month. The sample period is 1947-2010.

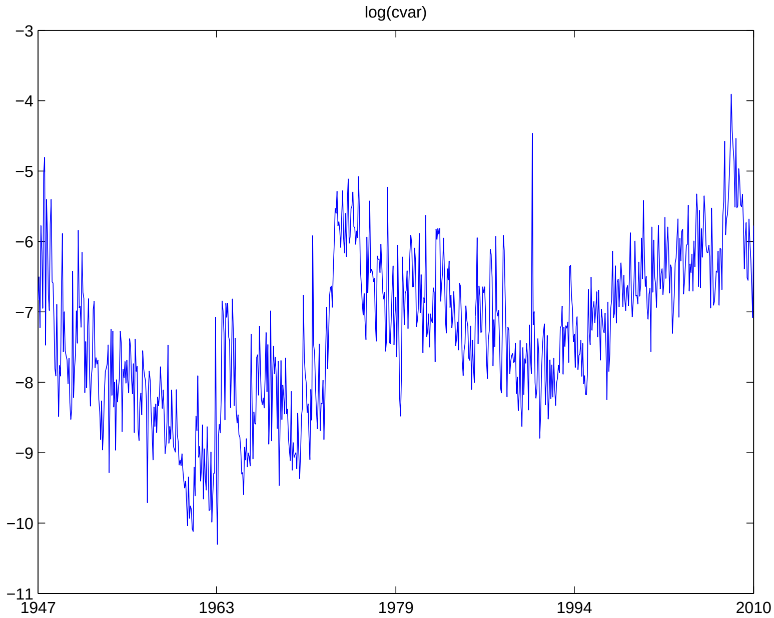


Figure 8: **Forecasts and actual values of max(ret,0) on raw industrials and metals spot price indexes.** The plots show the actual and the predicted value of the max between zero and the returns on the raw industrials and metals Commodity Research Bureau price indexes at quarterly frequency. Forecasts are generated out-of-sample and use the lagged growth in the money supply, lagged volatility and AR(1) as the predictor variable. The out-of-sample period is 1991-2010.

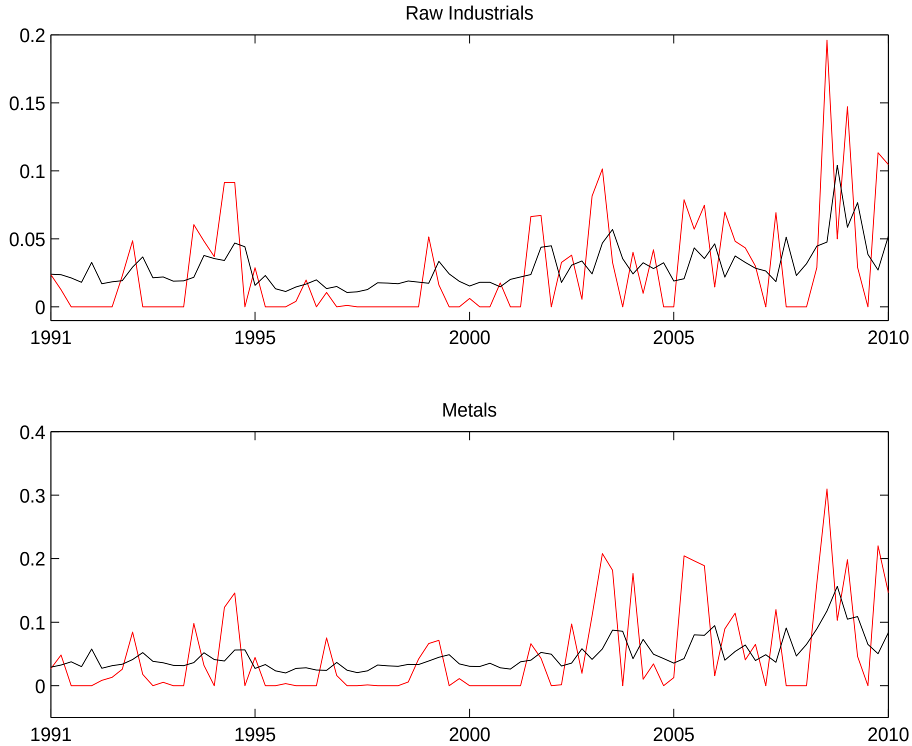


Table 1: **Summary statistics for commodity returns.** This table reports mean, standard deviation, coefficient of skew, coefficient of kurtosis, and the first-order autocorrelation (AR(1)) for commodity returns at the monthly (Panel A), quarterly (Panel B), and annual (Panel C) horizons over the sample period 1947-2010. Commodity prices use the Reuters/Jeffries CRB Commodity Research Bureau spot price indexes and are measured at the end of the month. The last two columns show the comparable values for stocks (tracked by the value-weighted CRSP index) and 10-year T-bonds. Panel D shows correlations between monthly return series above the diagonal and correlations between annual returns below the diagonal.

Panel A: Monthly

	Fats & Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
mean (%)	0.310	0.236	0.254	0.277	0.431	0.179	0.226	0.975	0.484
std (%)	6.610	3.778	2.840	5.289	4.329	3.161	2.669	4.208	2.084
skew	0.552	0.759	0.044	0.269	-0.186	0.280	0.267	-0.411	0.509
kurt	7.324	7.894	7.716	5.671	6.615	12.027	8.412	4.659	5.048
AR(1)	0.089	0.100	0.364	0.098	0.299	0.129	0.280	0.039	0.073

Panel B: Quarterly

	Fats & Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
mean (%)	0.841	0.643	0.813	0.754	1.432	0.524	0.676	2.979	1.466
std (%)	11.200	6.464	6.459	8.987	9.466	5.892	5.476	7.804	3.972
skew	0.268	0.255	0.806	0.160	0.030	1.229	0.241	-0.574	0.934
kurt	5.041	4.775	9.859	4.636	4.736	11.482	6.676	4.051	4.414
AR(1)	0.034	0.088	0.299	0.060	0.220	0.157	0.255	0.102	0.019

Panel C: Annual

	Fats & Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
mean (%)	3.148	2.559	3.936	2.938	6.928	2.284	3.006	12.218	5.964
std (%)	22.439	14.637	18.861	17.862	26.463	15.193	14.977	17.553	8.942
skew	1.395	1.192	1.449	0.548	1.017	1.401	1.503	-0.346	0.972
kurt	6.448	6.536	6.530	3.315	4.830	6.621	6.622	2.948	4.378
AR(1)	-0.076	0.136	-0.128	-0.120	-0.128	-0.075	-0.008	-0.049	-0.095

Panel D: Correlation matrix

	Fats & Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
Fats & Oils	-	0.758	0.507	0.783	0.195	0.290	0.751	0.013	-0.063
Foods	0.845	-	0.397	0.705	0.225	0.278	0.812	0.053	-0.062
Raw Industrials	0.765	0.610	-	0.553	0.781	0.555	0.842	0.130	-0.205
Livestock	0.768	0.665	0.783	-	0.238	0.258	0.751	0.046	-0.112
Metals	0.640	0.536	0.899	0.635	-	0.203	0.606	0.123	-0.162
Textiles	0.685	0.573	0.844	0.692	0.593	-	0.500	0.053	-0.150
Commodity	0.871	0.821	0.952	0.819	0.851	0.826	-	0.104	-0.155
Stock	-0.147	-0.274	0.169	-0.043	0.189	0.085	0.017	-	0.120
Bond	-0.176	-0.116	-0.364	-0.261	-0.466	-0.173	-0.309	-0.015	-

Table 2: **Univariate regression coefficient estimates.** This table reports slope coefficients estimated by OLS using commodity returns as the dependent variable and a constant and the (single) variable listed in the row as predictor. All regressions use non-overlapping returns data over the period 1947-2010. The predictor variables are the dividend-price ratio (dp), the 3-month T-bill rate (tbl), the long term return (ltr), the term spread (tms), the default return spread (dfr), inflation (infl), the investment-capital ratio (ik), commodity price volatility (cvol), growth in industrial production (ΔIND), money supply growth ($\Delta M1$), the change in the unemployment rate (ΔUN), and the one-period lagged return (AR(1)). P-values are computed by bootstrap generating data under the null $r_{t+1} = \alpha + \epsilon_{t+1}$. Stars indicate statistical significance: ***: significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Panel A: Monthly

	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
dp	-0.007	-0.003	-0.003	-0.005	-0.006*	-0.001	-0.003	0.009**	0.000
tbl	-0.014	-0.014	-0.062*	-0.034	-0.116**	-0.025	-0.041	-0.033	0.096***
ltr	-0.034	0.008	-0.119***	-0.069	-0.226***	-0.040	-0.071**	0.153***	0.060**
tms	0.111	0.013	0.167**	0.194	0.209*	0.078	0.102	0.140	0.096*
dfr	0.134	0.066	0.325***	0.435***	0.559***	0.204**	0.220***	0.109	-0.003
infl	1.065*	0.458	0.522**	0.551	0.517	0.012	0.493**	-0.656*	-0.262
cvol	0.020	0.023	0.056	-0.044	0.190**	0.108	0.029	-0.119	0.050
ΔIN	0.267	0.204	0.580***	0.267	0.756***	0.340***	0.421***	0.079	-0.127*
$\Delta M1$	0.054	0.034	0.094***	0.078*	0.108***	0.091***	0.067***	-0.036	0.011
ΔUN	0.009	0.011	-0.073***	-0.036	-0.114***	-0.015	-0.041*	0.025	0.032*
AR(1)	0.088**	0.099***	0.363***	0.097***	0.299***	0.129***	0.278***	0.039	0.072**

Panel B: Quarterly

	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
dp	-0.017	-0.011	-0.007	-0.012	-0.016	-0.002	-0.009	0.030**	0.000
tbl	-0.178	-0.062	-0.245*	-0.137	-0.408**	-0.095	-0.166	-0.080	0.319***
ltr	-0.078	0.057	0.004	-0.021	-0.033	0.115	0.021	0.137	0.010
tms	0.367	0.039	0.479*	0.424	0.588	0.247	0.301	0.447	0.250
dfr	0.333	0.220	0.476**	0.484*	0.783***	0.033	0.373**	0.542**	-0.072
infl	-1.744**	-0.557	-1.222***	-1.386**	-1.452**	-0.600	-0.949***	-0.479	0.335
ik	-1.490	0.136	-2.525**	-1.192	-3.616**	-1.295	-1.375	-3.089**	0.725
ΔIN	0.538	0.332*	0.645***	0.373	0.665**	0.381**	0.512***	-0.185	-0.075
$\Delta M1$	0.185	0.141	0.326***	0.284**	0.417***	0.256***	0.246***	-0.107	0.032
ΔUN	-0.105	-0.073	-0.102*	-0.053	-0.114	-0.065	-0.089*	0.117*	0.024
AR(1)	0.033	0.087	0.297***	0.058	0.220***	0.157**	0.252***	0.102	0.018

Panel C: Annual

	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
dp	-0.046	-0.043	0.001	-0.029	-0.046	0.009	-0.018	0.145***	-0.006
tbl	-1.042	-0.651	-1.524*	-0.921	-2.696**	-0.657	-1.095*	-0.253	1.159***
ltr	0.169	-0.063	0.431*	0.305	0.651**	0.228	0.220	0.205	-0.088
tms	1.690	1.226	3.091*	2.278	4.650**	1.830	2.292*	1.086	1.257
dfr	0.387	0.514	-0.317	0.109	-0.732	-0.099	0.081	-0.358	0.339
infl	-1.790*	-0.863	-1.864**	-1.408*	-2.672**	-1.022	-1.384**	-0.103	0.719*
ik	-13.388*	-3.163	-15.009**	-11.075*	-19.331**	-7.836	-9.646*	-10.079	3.203
cvol	0.638	0.447	0.737	0.616	1.655***	0.251	0.575	-0.076	0.020
ΔIN	-1.019*	-0.062	-1.363***	-1.022**	-1.330**	-0.982***	-0.791**	-0.367	-0.140
$\Delta M1$	1.028	0.926*	1.211*	1.055*	1.682*	0.867*	1.091**	-0.514	0.288
ΔUN	0.287**	0.035	0.392***	0.272**	0.384**	0.269***	0.232**	0.125	-0.004
AR(1)	-0.075	0.135	-0.128	-0.119	-0.128	-0.073	-0.008	-0.049	-0.094

Table 3: **Out-of-sample R^2 values for the univariate prediction models.** This table reports out-of-sample R^2-values (in percent) for univariate return prediction models that include a constant and the predictor variable listed in each row. The forecast evaluation period is 1991-2010. All forecasts are updated recursively, using an expanding estimation window. Returns are based on the Reuters/Jeffries CRB spot price indexes. Statistical significance is measured by bootstrap generating data under the null $r_{t+1} = \alpha + \epsilon_{t+1}$. Stars indicate statistical significance: ***: significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Panel A: Monthly

	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
dp	-0.388	-0.308	-2.747	-0.830	-1.066	-1.279	-1.663	-1.555	-1.463
tbl	-0.151	-0.099	0.874**	-0.022	0.997**	-0.047	0.415*	-0.712	-0.840
ltr	-1.074	-0.783	-0.972	-0.751	-0.119	-1.361	-2.050	-0.588	0.323
tms	-0.082	-0.234	0.607**	0.070	0.297	-0.083	0.224	-2.289	-0.076
dfr	-0.548	-0.799	4.325***	2.094***	4.500***	0.333*	1.536***	-0.648	-0.599
infl	0.609**	0.438*	-0.172	0.259	-0.587	-0.942	0.486*	-1.704	0.464*
cvol	-0.673	-0.632	-0.739	-0.910	-0.373	0.217	-0.933	0.110	-1.553
ΔIN	-0.193	0.314*	3.060***	-0.321	1.996***	0.142	2.122***	-0.494	-2.072
$\Delta M1$	-0.551	-0.664	1.593***	-0.324	0.931**	0.793**	-0.140	-0.184	-1.141
ΔUN	-0.089	-0.047	0.062	-0.134	-0.162	-0.133	-0.256	-0.858	-0.022
AR(1)	0.853**	0.313	9.139***	1.018**	7.189***	-7.282	5.279***	0.040	0.128

Panel B: Quarterly

	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
dp	-1.573	-1.132	-4.562	-2.701	-2.141	-6.014	-3.833	-3.541	-3.768
tbl	0.212	-0.195	2.515**	0.212	2.510**	0.876*	1.574*	-1.368	-1.224
ltr	-0.334	-0.111	-2.529	-1.369	-0.914	-6.988	-1.709	-3.550	-0.377
tms	0.014	-0.766	1.058*	0.173	0.460	0.528	0.535	-5.024	0.098
dfr	-2.776	-1.727	4.077***	-0.580	3.862***	-1.223	1.813**	0.313	-1.586
infl	5.137***	1.464*	7.673***	5.328***	3.821***	1.322*	6.391***	0.223	1.442*
ik	-0.195	-3.188	5.819***	-0.239	3.870***	2.662**	1.781*	-1.923	-1.709
ΔIN	-0.380	0.837	-2.855	-0.594	-2.399	-1.257	-0.644	-2.290	-1.216
$\Delta M1$	-0.864	-1.067	6.853***	0.645	3.941***	5.378***	3.255**	-0.811	-2.759
ΔUN	-0.313	0.629	-1.097	-0.713	-0.440	-0.422	-0.006	-2.217	-1.105
AR(1)	-0.273	-0.082	10.340***	-0.302	5.927***	4.549***	6.026***	-0.296	-0.482

Panel C: Annual

	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
dp	-9.272	-16.877	-4.761	-11.394	-3.771	-6.876	-9.357	-17.316	-7.524
tbl	4.837*	5.625*	13.460**	6.174*	12.870**	6.611*	13.002**	-3.425	1.097
ltr	-3.341	-2.811	-4.448	-0.418	1.839	-25.565	-10.076	-4.343	-1.346
tms	1.943	3.986	11.943**	7.615**	8.875**	9.130**	12.686**	-6.553	-6.047
dfr	-9.357	-6.847	-18.734	-13.906	-17.182	-17.513	-18.585	-19.775	5.167*
infl	6.227*	4.518*	9.746**	8.099**	8.704**	4.511*	9.551**	-0.436	2.545
ik	12.448**	-1.014	17.682***	9.849**	10.003**	9.811**	16.468***	-0.468	-6.388
cvol	2.758	6.873*	5.054*	6.016*	10.272**	-3.245	8.355**	-3.850	-11.143
ΔIN	16.136***	-15.030	18.684***	20.216***	8.286**	12.599**	19.132***	-5.594	-1.423
$\Delta M1$	6.194*	13.426**	15.490**	11.818**	7.347**	22.638***	20.624***	-4.546	-15.396
ΔUN	14.810***	-3.003	14.249**	17.173***	6.953*	10.287**	15.921***	-2.193	-0.730
AR(1)	-4.480	1.442	-2.620	0.117	-7.016	-1.632	-2.758	-4.833	-0.119

Table 4: **Improvement in predictive accuracy relative to the first-order autoregressive return model.** This table reports the marginal improvement in the out-of-sample R^2-value (in percent) of a bivariate return prediction model that includes a constant, the lagged return, and the predictor variable listed in each row, measured relative to the R^2-value of a model that only includes a constant and the lagged commodity return. For example, an R^2-value of 1% means that adding a particular predictor improves on the R^2-value of the pure autoregressive model. The forecast evaluation period is 1991-2010. All forecasts are updated recursively, using an expanding estimation window. Returns are based on the Reuters/Jeffries CRB spot price indexes. Statistical significance is measured by means of the Clark-West (2006) test for out-of-sample predictive accuracy, using the first-order autoregressive model as the benchmark. Stars indicate statistical significance: ***: significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Panel A: Monthly

	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
dp	-0.466	-0.352	-1.314	-0.837	-0.638	-0.740	-1.100	-1.353	-1.337
tbl	-0.147	-0.110	0.477	-0.042	0.570	-0.075	0.217	-0.616	-0.619
ltr	-0.891	-0.427	-0.517	-0.567	-0.569	-0.579	-0.910	-0.739	0.014
tms	-0.104	-0.237	0.184	0.026	0.013	-0.140	0.034	-2.051	0.087
dfr	-0.630	-0.811	1.018	1.705*	2.415*	-0.376	0.156	-0.706	-1.027
infl	0.331	0.167	-0.286	-0.053	-0.733	-0.321	-0.074	-1.428	0.290
cvol	-0.640	-0.574	-0.569	-0.904	0.018	0.170	-0.842	0.054	-1.524
ΔIND	-0.201	0.309	2.030	-0.301	1.403	0.806	1.591	-0.425	-1.590
$\Delta M1$	-0.516	-0.609	0.911*	-0.297	0.520	0.905	-0.090	-0.168	-0.980
ΔUN	-0.072	-0.007	-0.086	-0.155	-0.135	-0.188	-0.192	-0.919	0.010

Panel B: Quarterly

	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
dp	-1.711	-1.301	-3.058	-2.687	-2.037	-4.833	-3.069	-4.225	-3.709
tbl	0.213	-0.180	2.281	0.193	2.055	1.158	1.365	-1.101	-1.081
ltr	-0.487	0.054	-4.413	-1.671	-1.297	-8.163	-2.375	-2.698	-1.076
tms	-0.026	-0.738	0.118	0.023	0.033	0.526	0.046	-4.235	0.176
dfr	-2.852	-1.495	-0.634	-0.911	1.221	-1.562	0.123	-0.626	-1.917
infl	5.174**	1.411**	8.417*	5.287**	4.098*	1.512	6.439**	0.154	1.411
ik	-0.218	-2.753	4.564**	-0.217	3.245**	2.352*	1.876**	-1.423	-1.680
cvol	-1.759	-1.494	-1.061	-1.576	-0.286	-0.326	-1.401	-0.696	-4.408
ΔIND	-0.550	0.669	-3.861	-0.589	-3.217	-1.833	-1.580	-1.934	-1.152
$\Delta M1$	-0.926	-0.848	5.263**	0.668	3.054*	4.350*	3.059**	-0.790	-2.668
ΔUN	-0.399	0.509	-1.174	-0.661	-0.810	-0.654	-0.442	-1.712	-1.023

Panel C: Annual

	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
dp	-9.167	-17.053	-5.464	-12.601	-3.384	-7.490	-9.307	-15.806	-7.379
tbl	4.575	6.143	14.143**	5.946*	14.735**	5.901*	13.479**	-4.171	5.262*
ltr	-2.462	-5.064	-4.517	-2.119	3.523	-24.930	-8.431	-5.632	-5.080
tms	1.832	4.214	13.405**	9.460*	10.884**	8.884*	13.158**	-7.565	-0.622
dfr	-7.000	-9.572	-16.830	-11.121	-15.192	-16.430	-17.004	-16.652	2.976
infl	7.421*	6.833	9.826**	7.272**	9.639**	4.531	11.242**	-1.297	1.390
ik	12.478**	2.003	19.813***	9.396*	11.856***	10.271*	16.792***	-5.628	-7.120
cvol	5.197	0.518	10.128*	8.179	17.691*	-1.775	9.006	-3.052	-9.772
ΔIND	14.670*	-10.211	20.325**	19.075*	10.379**	13.506*	20.884**	-10.121	0.778
$\Delta M1$	6.236	12.148*	20.838***	17.099**	9.826**	26.474***	21.837***	-6.284	-13.542
ΔUN	15.004*	-0.823	16.354*	17.648*	9.369*	10.863	16.890*	-6.774	-0.747

Table 5: **Out-of-sample R^2 values for the univariate prediction models (levels).** This table reports out-of-sample R^2-values (in percent) for bivariate prediction models that include a constant, the lagged price and the predictor variable listed in each row: $P_{t+1} = \alpha + \gamma P_t + \beta x_t + \epsilon_{t+1}$. The forecast evaluation period is 1991-2010. All forecasts are updated recursively, using an expanding estimation window. Statistical significance is measured by bootstrap generating data under the null $P_{t+1} = \alpha + \beta P_t + \epsilon_{t+1}$. Stars indicate statistical significance: ***: significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Panel A: Monthly

	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity
dp	0.333	0.222	-0.650	0.204	-0.088	-0.463	-0.320
tbl	-1.438	-0.715	0.380*	-0.443	-0.108	-0.416	0.195
ltr	-0.699	-0.491	-0.121	-0.493	0.088	-0.984	-0.966
tms	0.116	-0.091	0.072	0.316	-0.258	0.080	-0.097
dfr	-0.620	-0.879	3.351***	1.906***	1.945***	-0.102	1.378***
infl	0.144	0.002	-0.255	-0.035	-0.415	-0.680	-0.037
cvol	-0.968	-0.596	-0.781	-0.857	-0.630	0.607**	-0.746
ΔIN	-0.032	0.374*	2.057***	-0.151	1.171***	0.175	1.652***
$\Delta M1$	-1.119	-1.003	0.438*	-0.729	0.018	0.151	-0.707
ΔUN	-0.051	-0.038	0.031	-0.108	-0.023	-0.111	-0.117

Panel B: Quarterly

	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity
dp	0.678	0.541	-1.145	0.206	-0.102	-2.251	-0.645
tbl	-2.253	-2.216	0.442	-1.075	-0.664	-0.237	-0.169
ltr	-0.532	0.038	-1.614	-0.765	-0.725	-4.641	-1.036
tms	0.551	-0.117	0.319	0.839	-0.548	1.618*	0.100
dfr	-3.553	-2.449	3.093**	-1.796	2.705**	-1.117	0.400
infl	3.386**	1.381*	4.862***	4.244***	2.947**	0.947*	4.690***
ik	0.078	-1.077	4.214***	0.613	1.778*	2.261*	2.254**
cvol	-1.000	-1.157	-1.422	-0.989	-1.377	0.240	-1.352
ΔIN	0.309	0.955*	-0.028	-0.094	-0.299	-0.245	0.799
$\Delta M1$	-1.899	-2.316	2.436**	-1.003	0.623	0.510	0.052
ΔUN	-0.150	0.322	-0.456	-0.510	-0.262	-0.305	-0.023

Panel C: Annual

	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity
dp	-0.740	-0.017	-1.825	-3.746	-0.368	-3.934	-1.955
tbl	-3.618	6.749*	4.891	1.902	-3.072	-0.389	7.223*
ltr	-8.116	-5.050	-5.427	-5.463	-2.883	-23.458	-9.066
tms	4.402*	5.092*	10.213**	10.194**	3.758	18.142***	9.515**
dfr	-11.912	-7.130	-21.366	-16.469	-19.566	-21.049	-18.642
infl	4.155	8.094*	4.731	3.891	0.961	4.900*	6.514*
ik	8.404**	-0.257	10.454**	8.655**	3.383	7.910**	10.402**
cvol	25.992***	26.095***	21.060***	22.481***	18.958**	13.823**	23.896***
ΔIN	15.894***	-3.733	12.979**	17.355***	4.268*	20.799***	11.315**
$\Delta M1$	-1.571	-5.394	9.801**	7.699**	2.744	17.091***	7.541*
ΔUN	10.307**	-2.428	7.783**	11.781**	1.040	12.810**	7.577**

Table 6: **Forecasting performance in recessions versus expansions.** This table compares the out-of-sample R^2 values of monthly and quarterly return prediction models in expansions versus recessions, defined by the NBER recession indicator. The forecast evaluation period is 1991-2010. All forecasts are updated recursively, using an expanding estimation window. Returns are based on the Reuters/Jeffries CRB spot price indexes. Statistical significance measures whether the average squared forecast error of a given model, measured relative to the constant return benchmark, is significantly different in recessions versus expansions. Stars indicate statistical significance: ***: significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Panel A: Monthly

A.1 Expansions

	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
dp	-0.372	-0.256	-3.986	-0.999	-1.083	-2.762	-2.391	-3.364	-1.738
tbl	-0.161	-0.094	2.037	0.077	1.973	0.235	1.255	-0.472	-0.919
ltr	-0.881	-0.882	-0.753	0.044	-1.547	-0.628	-2.434	-1.005	1.046
tms	0.061	-0.363	2.358	0.640	1.125	0.309	1.390	-2.496	0.010
dfr	0.015	-0.021	1.654	1.163	0.527	-0.461	0.813	-0.191	-0.397
infl	0.513	-0.021	-2.538	0.005	-1.820	-0.899	-1.258	0.209	0.283
cvol	-0.030	0.235	1.666	-1.019	3.466	0.850	1.249	-0.631	-1.302
ΔIN	-0.247	-0.013	-0.268	-0.593	-0.456	2.086	-0.417	-0.383	-0.669
$\Delta M1$	-0.515	-0.418	0.987	-0.028	-0.040	1.138	-0.145	0.197	-1.108
ΔUN	-0.043	0.028	0.021	-0.294	0.052	0.230	-0.587	-0.640	-0.142
AR(1)	-0.530	0.038	3.417	-0.837	3.659	-2.611	3.295	-0.562	0.409

A.2 Recessions

	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
dp	-0.420	-0.403	-0.994	-0.462	-1.038	-0.115	-0.832	3.112**	-0.414
tbl	-0.131	-0.109	-0.771	-0.240	-0.692	-0.268	-0.543	-1.333	-0.539
ltr	-1.453	-0.602	-1.283	-2.489	2.352	-1.936	-1.611	0.488	-2.426
tms	-0.366	-0.000	-1.870	-1.173	-1.137	-0.392	-1.105	-1.755	-0.409
dfr	-1.658	-2.211	8.106**	4.128*	11.379***	0.957	2.361	-1.827	-1.364
infl	0.797	1.273***	3.175***	0.813*	1.547***	-0.975	2.478***	-6.643	1.154
cvol	-1.938	-2.206	-4.144	-0.673	-7.023	-0.278	-3.423	2.027*	-2.509
ΔIN	-0.088	0.909*	7.771**	0.273	6.244**	-1.383	5.021**	-0.780	-7.411
$\Delta M1$	-0.621	-1.112	2.452*	-0.969	2.613**	0.523	-0.134	-1.169	-1.269
ΔUN	-0.180	-0.186	0.121	0.214	-0.535	-0.419	0.122	-1.421	0.435
AR(1)	3.577**	0.811	17.239***	5.073***	13.301***	-10.948	7.544*	1.598***	-0.938

Panel B: Quarterly

B.1 Expansions

	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
dp	-1.103	-0.616	-6.539	-2.532	-1.615	-6.735	-4.612	-8.107	-4.429
tbl	0.800	-0.067	5.858	0.930	4.713	1.131	4.154	-0.908	-1.773
ltr	-0.821	-0.156	-3.985	-2.025	-0.836	-5.351	-2.621	-2.020	-0.127
tms	0.709	-1.271	4.014	1.448	1.848	0.762	2.697	-5.091	1.016
dfr	-0.459	-0.634	4.569	3.210	1.863	-0.734	2.277	-1.555	-0.007
infl	1.822	0.523	-0.314	1.604	-0.530	-1.805	0.940	-0.428	-0.354
ik	-0.306	-4.638	7.304	-0.306	3.870	2.330	2.044	-5.468	-2.528
cvol	1.440	2.774	6.896	2.089	7.453	0.497	7.090	-0.801	-2.279
ΔIN	-1.454	-0.732	-3.114	-1.656	-1.922	1.007	-3.232	-1.366	-0.723
$\Delta M1$	-1.215	-1.409	4.155	0.169	0.773	3.618	1.190	1.483	-2.192
ΔUN	-0.857	-0.333	-0.132	-1.065	0.872	0.897	-0.487	-1.148	-0.392
AR(1)	-0.316	-0.268	11.092	-0.375	5.271	5.153	5.176	-2.334	-0.053

B.2 Recessions

	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
dp	-2.842	-2.353	-2.187	-3.016	-2.938	-0.796	-2.854	6.204*	-0.770
tbl	-1.372	-0.496	-1.501	-1.126	-0.831	-0.972	-1.669	-2.351	1.265
ltr	0.982	-0.006	-0.780	-0.147	-1.033	-18.836	-0.561	-6.814	-1.508
tms	-1.860	0.424*	-2.494	-2.203	-1.643	-1.168	-2.183	-4.879	-4.069
dfr	-9.034	-4.309	3.486	-7.650	6.894	-4.761	1.229	4.304	-8.747
infl	14.089***	3.686***	17.271***	12.271***	10.422***	23.973***	13.244***	1.614**	9.597***
ik	0.103	0.239	4.035*	-0.114	3.871**	5.067	1.451	5.644**	2.003
cvol	-9.654	-11.558	-11.083	-8.513	-9.537	-6.362	-12.316	0.991	-14.303
ΔIN	2.519	4.546***	-2.544	1.385	-3.123	-17.661	2.610	-4.263	-3.454
$\Delta M1$	0.082	-0.257	10.095***	1.531	8.746***	18.120	5.851**	-5.708	-5.336
ΔUN	1.155	2.903**	-2.257	-0.057	-2.431	-9.979	0.597	-4.498	-4.339
AR(1)	-0.156	0.358	9.437	-0.165	6.921	0.181	7.095	4.053**	-2.430

Table 7: **Multivariate out-of-sample prediction results:** This table reports the out-of-sample R^2-value for a range of multivariate model selection and estimation methods. AIC and BIC are the Akaike and Bayes Information Criteria which select the prediction model using penalized likelihood criteria, at each point searching across all possible combinations of predictor variables. Ridge regression includes all predictor variables in the forecasting model but shrinks, trough λ, the least squares coefficient estimate towards zero. Subset regression computes an equal-weighted average of forecasts considering all possible models with k predictor variables included. The set of predictor variables is identical to that listed in Table 2. All estimation and model selection is conducted recursively, using an expanding estimation window and 1991-2010 as the out-of-sample forecast evaluation period. Returns are based on the Reuters/Jeffries CRB spot price indexes. Statistical significance is measured by means of the Clark-West (2006) test for out-of-sample predictive accuracy, using the prevailing mean model, which only includes a constant, as the benchmark. Stars indicate statistical significance: ***: significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Panel A: Monthly

A.1 Model Selection

	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
AIC	-1.342	0.313	10.614	0.298	7.478	-9.348	5.403	-5.799	0.305*
BIC	-0.975	-0.618	9.417	-2.265	8.679	-11.329	6.403	-6.253	0.698

A.2 Ridge Regression

λ	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
0.5	-2.476	-1.472	10.449***	0.244	8.430***	-8.107	4.430***	-5.249	0.242
1	-2.471	-1.469	10.456***	0.247	8.435***	-8.095	4.436***	-5.240	0.245
2	-2.461	-1.461	10.469***	0.252	8.443***	-8.072	4.448***	-5.221	0.250
3	-2.452	-1.455	10.481***	0.256	8.451***	-8.049	4.459***	-5.202	0.255
4	-2.442	-1.448	10.493***	0.261	8.460***	-8.026	4.471***	-5.183	0.260
5	-2.433	-1.441	10.505***	0.266	8.468***	-8.003	4.482***	-5.164	0.264
10	-2.387	-1.408	10.563***	0.288	8.507***	-7.892	4.536***	-5.073	0.280
20	-2.301	-1.349	10.663***	0.329	8.577***	-7.682	4.633***	-4.901	0.291
50	-2.076	-1.203	10.885***	0.431	8.739***	-7.134	4.854**	-4.449	0.235
100	-1.781	-1.029	11.085***	0.552	8.899***	-6.399	5.082**	-3.861	0.060
150	-1.555	-0.903	11.163***	0.637	8.974***	-5.808	5.210**	-3.412	-0.102
200	-1.376	-0.805	11.170***	0.700	8.993***	-5.316	5.280**	-3.057	-0.230
1000	-0.419	-0.272	9.242***	0.862	7.504***	-2.107	4.605**	-1.153	-0.512

A.3 Subset Regression

k	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
1	-0.033	-0.039	3.336***	0.342	2.658***	-0.234	1.637**	-0.228	-0.095
2	-0.110	-0.102	5.800***	0.570	4.649***	-0.636	2.848**	-0.490	-0.233
3	-0.228	-0.187	7.596***	0.706	6.118***	-1.167	3.722**	-0.788	-0.362
4	-0.384	-0.291	8.882***	0.768	7.179***	-1.801	4.331**	-1.126	-0.447
5	-0.577	-0.412	9.775***	0.773	7.919***	-2.517	4.728**	-1.507	-0.467
6	-0.807	-0.551	10.363***	0.734	8.407***	-3.302	4.955**	-1.934	-0.414
7	-1.073	-0.705	10.711***	0.664	8.693***	-4.148	5.045**	-2.417	-0.292
8	-1.374	-0.876	10.866***	0.572	8.816***	-5.052	5.022**	-2.968	-0.120
9	-1.710	-1.061	10.860***	0.467	8.801***	-6.012	4.902**	-3.607	0.065
10	-2.079	-1.261	10.715***	0.356	8.668***	-7.032	4.700**	-4.359	0.211
11	-2.481	-1.476	10.443***	0.242	8.426***	-8.119	4.424***	-5.259	0.238

Panel B: Quarterly

B.1 Model Selection

	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
AIC	-5.140	-11.730	12.763	-5.412	5.974	-5.186	10.330	-14.699	-0.182*
BIC	0.111	0.000	-11.205	-3.519	-10.697	-6.364	-5.151	-12.589	1.923

B.2 Ridge Regression

λ	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
0.5	-8.134	-5.527	10.947***	-6.451	8.772***	-13.050	7.736**	-10.083	-10.078
1	-8.052	-5.450	11.103***	-6.352	8.858***	-12.730	7.866**	-10.013	-9.871
2	-7.894	-5.300	11.402***	-6.160	9.021***	-12.119	8.114**	-9.874	-9.484
3	-7.741	-5.157	11.681***	-5.977	9.174***	-11.541	8.347**	-9.740	-9.130
4	-7.594	-5.021	11.944***	-5.801	9.316***	-10.994	8.565**	-9.609	-8.804
5	-7.451	-4.891	12.191***	-5.633	9.448***	-10.476	8.770**	-9.482	-8.504
10	-6.809	-4.319	13.224***	-4.892	9.993***	-8.248	9.626**	-8.896	-7.304
20	-5.788	-3.466	14.579***	-3.771	10.672***	-5.074	10.741**	-7.918	-5.848
50	-3.892	-2.090	16.071***	-1.872	11.284***	-0.338	11.923**	-5.926	-4.214
100	-2.340	-1.180	16.079***	-0.500	11.034***	2.395	11.847**	-4.084	-3.447
150	-1.533	-0.780	15.460***	0.138	10.513***	3.343	11.293**	-3.028	-3.065
200	-1.043	-0.559	14.745***	0.490	9.975***	3.711*	10.689**	-2.342	-2.778
1000	0.195	-0.014	7.886***	0.901	5.226**	2.593*	5.483**	-0.195	-1.076

B.3 Subset Regression

k	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
1	0.209	-0.060	4.283***	0.527	2.779**	1.351*	2.846**	-0.042	-0.517
2	0.245	-0.170	7.585***	0.841	4.953**	2.327*	5.098**	-0.316	-1.046
3	0.118	-0.329	10.088***	0.963	6.626**	2.957	6.862**	-0.752	-1.546
4	-0.164	-0.533	11.957***	0.914	7.897**	3.269	8.238**	-1.288	-1.992
5	-0.592	-0.781	13.340***	0.714	8.856***	3.277	9.314**	-1.890	-2.374
6	-1.161	-1.075	14.353***	0.377	9.577***	2.968	10.156**	-2.550	-2.704
7	-1.870	-1.426	15.056***	-0.101	10.111***	2.285	10.792**	-3.287	-3.029
8	-2.727	-1.856	15.446***	-0.747	10.472***	1.115	11.197**	-4.148	-3.444
9	-3.752	-2.408	15.436***	-1.611	10.628***	-0.722	11.284**	-5.193	-4.103
10	-4.975	-3.147	14.852***	-2.779	10.492***	-3.493	10.892**	-6.493	-5.239
11	-6.443	-4.169	13.425***	-4.371	9.916***	-7.555	9.776**	-8.123	-7.166
12	-8.217	-5.607	10.785***	-6.553	8.682***	-13.379	7.601**	-10.155	-10.294

Panel C: Annual

C.1 Model Selection

	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
AIC	6.565	22.597	22.595	29.393	26.251	6.807	38.418	-57.660	40.517
BIC	0.000	0.000	18.264	11.804	2.111	10.287	30.521	-40.457	40.018

C.2 Ridge Regression

λ	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
0.5	-2.635	17.729*	23.439**	32.078**	30.197**	9.492**	26.831***	-54.765	13.828***
1	1.039	18.977*	26.831**	32.633**	31.651**	11.380**	29.876***	-53.011	18.686***
2	6.121*	20.249*	31.093**	33.060**	33.229**	13.921**	33.526***	-49.949	24.331***
3	9.386*	20.622*	33.543**	33.013**	33.839**	15.460**	35.449***	-47.336	27.087***
4	11.580*	20.539*	35.021**	32.739**	33.950**	16.410**	36.464***	-45.056	28.326***
5	13.093*	20.214*	35.923**	32.352**	33.789**	16.995**	36.957***	-43.036	28.705***
10	16.044*	17.683	36.867**	30.122**	31.723**	17.606**	36.457***	-35.438	26.091***
20	16.084*	13.805	35.009**	26.794**	27.745*	16.598*	33.305**	-26.406	19.150**
50	13.763*	9.516	30.113**	22.155**	21.564*	14.865*	27.688**	-14.684	9.843*
100	11.437*	7.168	25.239**	18.368**	16.841*	13.597*	22.896**	-8.070	5.356
150	9.876*	5.890	21.850**	15.822**	14.056*	12.451*	19.690**	-5.426	3.669
200	8.696*	5.013	19.264**	13.899**	12.113*	11.384*	17.278**	-4.040	2.783
1000	2.958*	1.481	6.585**	4.672**	3.837*	4.381*	5.787**	-0.738	0.548

C.3 Subset Regression

k	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
1	4.884*	2.004	10.618**	7.775**	6.159**	6.535*	9.271**	-1.532	0.645
2	8.238*	3.638	18.005**	13.289**	11.026**	10.327*	16.090**	-3.611	2.040
3	10.451*	4.978	23.126**	17.117**	14.929**	12.464*	21.024**	-6.182	4.289
4	11.885*	6.218	26.866**	19.863**	18.205**	13.911*	24.734**	-9.189	7.469*
5	12.813*	7.614	29.847**	22.060**	21.133**	15.297*	27.783**	-12.608	11.581**
6	13.360*	9.391	32.356**	24.098**	23.882*	16.833*	30.510**	-16.456	16.455**
7	13.468*	11.643	34.347**	26.175**	26.491*	18.349**	32.961***	-20.802	21.609**
8	12.877*	14.244	35.503**	28.283**	28.855*	19.403**	34.880***	-25.777	26.133**
9	11.137	16.790*	35.304**	30.225**	30.721*	19.412**	35.726***	-31.572	28.659***
10	7.648	18.588*	33.057**	31.657**	31.659*	17.756**	34.699***	-38.440	27.458***
11	1.695	18.672*	27.868**	32.130**	31.033**	13.814**	30.716***	-46.691	20.631***
12	-7.550	15.776*	18.477**	31.108**	27.972**	6.947**	22.252***	-56.712	6.265***

Table 8: **Predictability of realized commodity variance:** This table shows results for the logarithm of the realized commodity price variance computed as the sum of squared daily returns over the month (Panel A), the quarter (Panel B) or the year (Panel C). The first column shows full-sample OLS estimates of the slope coefficient, β_2, on the lagged covariates from a model $log(cvol^2_{t+1}) = \beta_0 + \beta_1 * log(cvol^2_t) + \beta_2 * x_t + \epsilon_{t+1}$. The second column shows the out-of-sample R^2 value computed over the sample 1991-2010. For the AR(1) model, the out-of-sample R^2 value is measured relative to a constant volatility benchmark. The third and fourth columns report out-of-sample R^2-values separately for recessions and expansions. Stars indicate statistical significance using the Clark-West (2007) statistic. ***: significant at the 1% level; **: significant at the 5% level; *: significant at the 10% level.

Panel A: Monthly

	β	$OoSR^2$	$OoSR^2_{Expan}$	$OoSR^2_{Recess}$
dp	-0.123***	-1.449	-3.115	1.825*
tbl	0.633	-4.198	-5.203	-2.222
ltr	-0.964	0.125	0.462	-0.536
tms	4.403***	1.332**	0.691	2.592**
dfr	-1.174	-0.450	-0.521	-0.310
infl	10.870*	-5.838	-5.605	-6.297
ΔIN	-2.384	0.277	-0.250	1.314***
$\Delta M1$	1.158**	-3.897	-6.989	2.178**
ΔUN	0.250	-0.034	-0.235	0.362***
AR(1)	0.811***	72.695***		

Panel B: Quarterly

	β	$OoSR^2$	$OoSR^2_{Expan}$	$OoSR^2_{Recess}$
dp	-0.146**	1.411	0.060	2.843*
tbl	0.604	-4.189	-8.602	0.484
ltr	0.264	-0.324	-0.038	-0.626
tms	3.613*	0.540	0.537	0.543
dfr	-2.364	0.704	1.351	0.020
infl	5.106	-4.424	-17.504	9.426***
ik	15.188**	-0.996	-2.510	0.605
ΔIN	-0.758	-0.145	-0.108	-0.183
$\Delta M1$	0.874	-5.241	-11.893	1.802*
ΔUN	0.191	-0.275	-0.446	-0.093
AR(1)	0.844***	74.740***		

Panel C: Annual

	β	$OoSR^2$	$OoSR^2_{Expan}$	$OoSR^2_{Recess}$
dp	-0.278***	2.252	-	-
tbl	0.978	-5.514	-	-
ltr	1.278**	5.088	-	-
tms	1.178	-1.479	-	-
dfr	-3.654***	0.285**	-	-
infl	1.555	-4.151	-	-
ik	39.200**	2.763	-	-
ΔIN	0.388	-0.533	-	-
$\Delta M1$	0.340	-17.576	-	-
ΔUN	-0.051	-1.095	-	-
AR(1)	0.828***	67.659***		

Table 9: **Predictability of min(0,r_{t+1})/max(0,r_{t+1}).** This table shows results from regressions using min(0,r_{t+1})/ max(0,r_{t+1}) as the dependent variables where returns are computed at monthly (Panel A), quarterly (Panel B) and annual (Panel C) frequency. Slope coefficients are estimated by OLS using min(0,r_{t+1})/max(0,r_{t+1}) as the dependent variables and a constant, the lagged values of volatility, the AR(1) and the (single) variable listed in the row as predictors. For AR(1) and cvol slopes are computed from univariate regressions. Stars indicate statistical significance using Newey-West standard errors (with one lag). Out-of-sample R^2 values are computed over the sample 1991-2010 and measured relative to a benchmark model that includes a constant, lagged cvol and lagged returns. For the AR(1) and the cvol models, the out-of-sample R^2 value is measured relative to a constant volatility benchmark. Stars indicate statistical significance using the Clark-West (2007) statistic. ***: significant at the 1% level; **: significant at the 5% level; *: significant at the 10% level

	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
Panel A: Monthly																		
	min(0,r_{t+1})									**max(0,r_{t+1})**								
	Slopes									**Slopes**								
dp	-0.000	-0.003*	-0.003**	-0.004	-0.004**	-0.003**	-0.003**	0.003	0.000	-0.006	0.000	0.001	-0.001	0.001	0.002*	0.000	0.005**	0.000
tbl	0.061	-0.005	-0.004	0.030	-0.041	0.013	-0.006	-0.026	-0.028*	-0.086	-0.008	-0.044**	-0.066	-0.054*	-0.035	-0.027	-0.003	0.113***
ltr	0.024	0.021	-0.013	0.011	-0.097**	2.739	0.004	0.048	-0.003	-0.037	-0.006	-0.035	-0.059	-0.068**	-0.007	-0.034	0.112***	-0.078
tms	0.038	0.028	0.073*	0.128*	0.083	-0.021	0.055	0.093	0.027	0.059	-0.024	0.038	0.066	0.035	0.055	0.018	0.081	0.061
dfr	0.194	0.081	0.122	0.253*	0.299*	-0.000	0.115	0.119	0.034	-0.108	-0.027	0.092*	0.153	0.165**	0.142	0.042	-0.033	0.042
infl	0.363	-0.308	0.059	-0.172	0.202	-0.096	-0.132	-0.231	-0.212*	0.316	0.626**	0.044	0.561*	-0.057	-0.114	0.262	-0.359	-0.037
ΔIN	0.031	0.070	0.171*	0.130	0.433***	0.158***	0.129	0.097	0.045	0.200	0.131	0.240***	0.105	0.233**	0.161	0.195***	-0.064	-0.116*
$\Delta M1$	0.069**	0.024	0.032**	0.054**	0.029	-0.007	0.025**	-0.003	-0.028***	-0.027	0.005	0.034**	0.023	0.044*	0.076***	0.026*	-0.022	0.030**
ΔUN	0.013	0.007	-0.006	-0.011	-0.045**	-0.017	0.002	-0.000	-0.008	0.007	0.008	-0.021	-0.016	-0.027	0.008	-0.018	0.038	0.028**
cvol	-0.402***	-0.223***	-0.146**	-0.295**	-0.158	-0.113**	-0.172***	-0.192**	-0.031	0.422***	0.247***	0.202***	0.250***	0.349***	0.221***	0.202***	0.072	0.082*
AR(1)	0.218***	0.159***	0.340***	0.153***	0.261***	0.123*	0.318***	0.144**	0.034	0.092**	0.097**	0.349***	0.060*	0.265***	0.247***	0.263***	-0.036	0.178***
	OsS R^2									**OsS R^2**								
dp	-1.890	0.455	-1.996	-1.696	-0.945	-0.835	-0.646	-1.455	-0.993	0.458	-0.510	0.130	-0.387	-0.527	0.737*	-0.321	-2.749	-0.567
tbl	-0.988	-0.419	-0.383	-0.750	-0.438	-0.331	-0.384	-0.819	-4.629	0.114	-0.261	0.542	0.507	0.469	0.229	0.040	-0.397	-5.446
ltr	-0.479	-0.287	-0.082	-0.402	1.095	-0.153	-0.240	-0.345	-0.372	-0.884	-0.616	-1.615	-0.448	-1.601	-1.092	-1.878	-0.816	-4.906
tms	-0.134	-0.051	-0.261	0.166	-0.495	-0.216	0.052	-0.994	-1.189	-0.140	-0.171	0.017	-0.138	-0.157	0.098	-0.162	-1.924	0.592
dfr	0.106	-0.675	0.086	1.405	3.539**	-1.262	0.151	-0.790	-0.516	-0.392	-0.398	0.059	0.692	0.365	0.250	-0.541	-0.351	-1.682
infl	-0.131	0.025	-0.733	-1.362	-1.007	-0.076	-0.079	-1.890	-1.625	0.003	2.123**	-0.396	0.340	-0.529	-0.558	0.456	-1.717	-1.156
ΔIN	-0.271	-0.019	2.028*	-0.302	4.385*	1.494***	1.047	-0.019	0.455**	-0.120	0.202	1.115*	-0.246	0.089	-0.139	0.679	-0.391	-1.788
$\Delta M1$	-0.032	-1.160	-1.559	-1.275	-0.669	-0.777	-1.667	-0.359	0.328	-0.087	-0.232	1.584**	-0.139	0.873**	3.911**	0.494	-0.125	-1.887
ΔUN	-0.080	-0.080	-0.147	-0.045	-0.195	0.195	-0.071	-0.473	0.267*	-0.100	-0.091	0.086	-0.294	0.053	-0.176	-0.484	-0.327	1.116**
cvol	3.174*	0.433	0.626	2.030	0.837	-0.440	0.976	3.324**	0.389	3.113***	0.608**	4.054***	3.245***	5.904***	4.491**	2.484***	-0.555	-0.611
AR(1)	6.695**	3.597**	9.547**	2.681	2.821**	-3.834	12.978**	2.416*	-0.127	0.159	-0.237	8.405***	0.245	7.190***	-2.015	0.914**	-0.500	0.167

Panel B: Quarterly

	min(0,r_{t+1})									max(0,r_{t+1})								
	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
Slopes																		
dp	-0.011	-0.008*	-0.009*	-0.010	-0.011	-0.012**	-0.009**	0.010*	0.001	-0.002	-0.000	0.005	0.001	0.001	0.010	0.003	0.018**	0.000
tbl	0.042	-0.017	-0.056	0.006	-0.120	-0.033	-0.037	-0.050	0.008	-0.231	-0.047	-0.177**	-0.163	-0.258**	-0.077	-0.124*	-0.014	0.300***
ltr	-0.017	0.042	0.088	0.020	0.091	0.112***	0.064	0.008	-0.021	-0.054	0.024	0.028	-0.023	0.002	0.051	0.033	0.120	-0.205
tms	0.168	-0.035	0.191	0.212	0.095	0.172	0.059	0.176	0.007	0.096	-0.006	0.160	0.098	0.231	0.083	0.145	0.339	0.182
dfr	0.453	0.225	0.267	0.381	0.442	0.006	0.223	0.335**	0.027	-0.135	-0.000	0.053	0.084	0.184	-0.050	0.066	0.128	-0.054
infl	-0.677*	-0.568**	-0.673***	-0.813**	-0.685*	-0.498*	-0.601***	-0.310	-0.045	-1.229***	-0.074	-0.722*	-0.689*	-1.022*	-0.225	-0.469*	-0.077	0.313
ik	-1.206	-0.194	-0.882*	-1.085	-1.048	-0.261	-0.608	-1.350**	-0.057	-0.329	0.236	-1.463**	-0.128	-2.339**	-0.971	-0.740	-1.408	0.744
ΔIN	0.160	0.091	0.168*	0.215	0.416**	-0.015	0.140*	0.122	0.079	0.475	0.293**	0.380	0.218	0.260	0.329	0.318	-0.387**	-0.095
$\Delta M1$	0.191**	0.126**	0.104**	0.163**	0.124	0.045	0.099**	-0.021	-0.039	-0.037	-0.009	0.145*	0.089	0.190**	0.167**	0.093	-0.055	0.057
ΔUN	-0.019	-0.014	-0.023	-0.036	-0.080	0.018	-0.014	-0.021	-0.013	-0.094	-0.062**	-0.038	-0.017	-0.012	-0.063	-0.046	0.151***	0.024
cvol	-0.262	-0.156	-0.105	-0.116	-0.234	-0.036	-0.136	-0.236*	-0.016	0.481***	0.326**	0.344***	0.299**	0.696***	0.143*	0.332***	0.025	0.077
AR(1)	0.083	0.120	0.185**	0.132*	0.164	0.143	0.205**	0.103	-0.005	0.072	0.138	0.312***	0.028	0.292***	0.223***	0.303***	0.130**	0.121*
OsS R^2																		
dp	-6.114	-1.505	-10.085	-6.857	-4.299	-6.916**	-5.980	-3.133	-1.630	-1.678	-2.217	0.429	-2.203	-1.903	6.473***	-0.958	-4.675	-2.215
tbl	-1.267	-1.367	-0.567	-0.943	-1.292	-0.367	-0.556	-2.559	-2.170	-0.580	-1.203	0.847	0.009	2.311	-2.156	-0.086	-1.089	-1.613
ltr	-0.660	0.284	-1.767	-0.729	-0.121	-17.149	0.279	-1.325	-1.788	-0.495	-0.602	-3.853	-1.543	-1.557	-1.097	-3.719	-0.592	-5.668
tms	-0.013	-1.711	-1.081	0.366	-0.870	-0.361	-0.212	-1.578	-1.168	-0.535	-0.650	-0.065	-0.546	-0.084	-0.287	-0.709	-2.677	1.049
dfr	1.176	1.841	3.532*	2.363*	4.272*	-0.920	1.942	2.295	-1.141	-1.185	-2.160	-3.370	-2.745	-1.986	-1.930	-3.975	-2.991	-2.264
infl	2.437**	5.135**	4.979**	5.106***	3.188**	3.816**	5.253**	-0.690	-17.137	3.753*	-0.880	3.750	2.116	3.484	-2.478	2.567	-1.624	2.301*
ik	0.414	-3.225	1.076	1.273*	0.392	-0.259	0.791*	-0.595	-2.025	-0.676	-1.033	4.770*	-1.250	4.560**	3.132*	1.215	-2.635	-1.692
ΔIN	0.207	0.018	1.137	0.884	1.629	-0.119	0.636	0.392	0.943	-0.099	2.391**	-4.679	-0.510	-2.344	-0.545	0.355	0.188	-0.583
$\Delta M1$	1.358**	0.925*	-0.443	1.740**	-0.097	-4.535	-0.105	-1.501	0.553	-0.776	-0.817	5.638**	-0.628	2.909*	10.457***	2.095*	-1.374	-1.852
ΔUN	-0.205	-0.157	0.421	0.164	1.302*	-0.519	0.100	0.079	0.841	-0.204	1.494**	-2.194	-0.690	-0.557	-1.186	-0.104	1.542	-0.406
cvol	0.341	-2.455	-2.464	-2.199	-0.795	-6.734	-2.648	4.077*	-1.447	2.827*	0.202	5.687*	2.346	14.883***	-7.115	5.436**	-2.976	-4.311
AR(1)	0.315	1.302	2.260	2.261*	0.938	0.369	2.318	1.405	-0.227	-2.018	-3.441	8.505***	-1.002	12.145***	6.725**	-1.125**	-4.003	-3.766

Panel C: Annual

	min(0,r_{t+1})									max(0,r_{t+1})								
	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
Slopes																		
dp	-0.020	-0.028	-0.024	-0.020	-0.012	-0.020	-0.020	0.045**	0.002	-0.002	-0.010	0.046	0.009	-0.006	0.035	0.017	0.103***	-0.007
tbl	0.168	-0.186	-0.227	0.212	-0.302	-0.182	-0.274	-0.002	0.140**	-1.396**	-0.539*	-1.333**	-1.222***	-2.547***	-0.489	-0.873**	-0.273	1.042**
ltr	0.070	-0.015	0.153*	0.134**	0.128	0.055	0.082	0.057	-0.013	0.051	-0.032	0.253**	0.149	0.314	0.176	0.152	0.167	-0.306
tms	0.245	0.789*	1.332***	0.773**	1.580**	0.866*	0.901***	0.607	0.087	0.828	0.337	1.185	0.965	1.610	0.895	1.024*	0.647	1.437**
dfr	0.036	0.168	0.259	0.100	0.713**	0.069	0.197	0.050	0.098*	0.434	0.334*	-0.461	0.065	-0.975*	-0.161	-0.106	-0.387	0.238
infl	-0.476	-0.415	-0.612**	-0.426	-0.517*	-0.524*	-0.602***	-0.114	0.133	-1.919**	-1.050**	-1.732**	-1.455***	-3.014***	-0.756	-1.301**	-0.021	0.619
ik	-3.414	-0.558	-4.416**	-2.871	-5.076*	-2.925	-2.881**	-4.990**	-0.508	-10.663	-3.517	-10.684	-8.352*	-14.394**	-4.984	-7.077	-5.817	3.672
ΔIN	-0.434	0.071	-0.526***	-0.388	-0.237	-0.463**	-0.301*	-0.192	-0.040	-0.474	-0.101	-0.750	-0.548	-0.336	-0.657	-0.472	-0.368	-0.139
$\Delta M1$	0.571**	0.392**	0.646**	0.706***	1.017**	0.305*	0.444**	0.223	-0.004	0.215	0.382	0.484	0.205	0.510	0.541	0.499	-0.829*	0.314
ΔUN	0.082	-0.028	0.120***	0.064	0.078**	0.093*	0.069**	0.032	0.004	0.176	0.060	0.245*	0.184	0.189	0.182	0.151	0.138*	-0.007
cvol	0.027	-0.038	0.045	0.207*	0.093	-0.024	-2.695	-0.141	0.011	0.610*	0.485**	0.692*	0.409	1.562**	0.275	0.575**	0.064	0.008
AR(1)	0.172	0.107	0.003	0.103	-0.177**	0.001	0.109	0.088	-0.083	-0.041	0.225	-0.010	-0.027	-0.003	0.041	0.082	-0.101	-0.048
OsS R^2																		
dp	-48.857	-13.819	-31.370	-36.562	-35.060	-27.281	-19.780	-2.122	-12.968	-6.347	-14.913	3.639*	-4.988	-3.418	6.862*	-1.336	-33.059	-6.488
tbl	-6.296	-0.864	0.867	-7.684	-0.247	0.340	4.220	-3.574	4.188	16.983**	5.743	17.810*	20.657*	26.438*	3.614	18.300*	-12.522	3.970*
ltr	-1.295	-1.912	-16.252	-4.993	-8.618	-25.619	-10.944	-0.471	-3.096	-6.609	-13.152	-1.383	-0.544	0.975	-18.004	-10.777	-5.698	3.608**
tms	-0.425	11.290**	10.562***	2.050*	7.282***	3.891	6.616***	-2.420	-2.579	-0.820	-6.447	-0.565	1.570	-0.146	3.558	-0.601	-6.078	2.470*
dfr	-9.033	-21.277	-7.007	-4.673	6.994**	-8.677	-14.603	-14.672	0.251	-3.514	-2.431	-4.859	-16.829	0.479	-14.925	-13.421	-17.083	2.345
infl	-0.090	16.469**	8.840**	2.771	-0.310	17.550**	14.000**	-3.621	1.826	11.532**	9.548*	7.269	17.379*	28.913*	-8.381	11.652	-6.701	1.050
ik	1.318	-10.865	7.555**	-1.491	5.573**	5.148	5.308**	7.970**	-4.973	18.854**	5.127	19.043**	15.821*	12.243**	11.100**	21.885***	-14.883	-3.891
ΔIN	3.983*	-10.518	2.242	2.550	2.028*	0.182	1.420	-0.956	0.028	5.721	-1.713	-1.444	10.766	-0.946	8.405**	6.963*	-10.026	1.116
$\Delta M1$	-4.479	-14.732	14.493**	12.940*	13.589**	-2.819	10.007**	-0.663	-3.769	-1.983	-3.680	1.876	-1.241	-2.890	16.142***	3.601	-12.366	-10.727
ΔUN	4.533*	-9.188	2.855	1.761	2.247	-3.655	2.473	0.032	-0.804	11.428*	2.859	3.540*	17.536*	-0.141	12.482**	10.156*	-8.617	-0.951
cvol	-4.219	-28.885	-3.872	3.709	-2.283	-17.104	-7.754	-2.558	-16.408	10.186	20.571*	11.134*	1.983	15.942*	0.317	20.747*	-5.751	-7.345
AR(1)	-4.868	2.817	-3.499	-6.863	0.489	-1.318	-6.199	-5.009	1.052	-5.033	5.998	-1.706	-1.847	-3.696	0.038	1.656	-6.257	-2.494