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# Forecasting commodity price indexes using macroeconomic and financial predictors

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ABSTRACT

Using a long sample of commodity spot price indexes over the period 1947–2010, we examine the out-of-sample predictability of commodity prices by means of macroeconomic and financial variables. Commodity currencies are found to have some predictive power at short (monthly and quarterly) forecast horizons, while growth in industrial production and the investment–capital ratio have some predictive power at longer (yearly) horizons. Commodity price predictability is strongest when based on multivariate approaches that account for parameter estimation error. Commodity price predictability varies substantially across economic states, being strongest during economic recessions.


## 1. Introduction

Commodity prices are widely believed to influence price levels more broadly, and thus are of interest to central banks, policy makers, firms and consumers whose decisions depend on their expectations of future inflation.[1] It is therefore of interest to explore whether commodity prices can be predicted, and, if so, by which variables. This paper considers the question of whether macroeconomic and financial variables are useful in this regard. We study both in-sample and out-of-sample forecasts, and consider evidence across monthly, quarterly, and annual horizons, as well as across recession and expansion states.

Why might macroeconomic and financial variables help to forecast movements in commodity prices? The predictability of commodity spot prices can be expected to be driven by time-varying storage costs and convenience yields. Both of these can be influenced by the state of the economy through short-term mismatches between demand and supply for commodities, and through financing costs. Time varying risk-premia form another possible source of predictability for commodity prices.[2]

With few exceptions, relatively little empirical work has been undertaken on the predictability of commodity spot prices by means of macroeconomic and financial variables. Chen, Rogoff, and Rossi (2010) study predictability in an aggregate commodity price index which comprises more than forty traded products. Using five commodity currencies, they find evidence that exchange rates predict commodity prices both in-sample (after accounting for parameter instability) and out-of-sample.

Groen and Pesenti (2011) study the predictability of ten spot price indexes in an out-of-sample experiment.

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1 Groen and Pesenti (2011) quote Federal Reserve Chairman Bernanke as "underscoring the importance for policy of both forecasting commodity price changes and understanding the factors that drive those changes."

2 Acharya, Lochstoer, and Ramadorai (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 affects 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.

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They conclude that neither commodity exchange rates (as per Chen et al., 2010) nor a broad cross-section of macroeconomic variables produce overwhelmingly strong evidence of spot price predictability when compared with random walk or autoregressive benchmarks.

The predictability of commodity futures prices has attracted more interest. Bessembinder and Chan (1992) find that the T-bill yield, dividend yield and junk bond premium have limited predictive power over movements in agricultural, metal, and currency futures prices. Hong and Yogo (2012) find evidence of limited in-sample predictability of returns on commodity futures. Predictable changes in commodity futures prices are driven mostly by time-varying risk premia. However, given the weak evidence of predictability of commodity futures prices, predictable variations in risk premia are likely to be only a small component of any predictable dynamics in commodity spot prices.

Our study focuses on four questions. First, do macroeconomic and financial variables possess predictive power over commodity prices? To address this issue, we explore out-of-sample predictability for a range of commodity spot price indexes over the 40-year period 1971–2010. Our analysis considers financial variables from the literature on stock return predictability, in addition to macroeconomic predictors such as inflation, money supply growth, growth in industrial production, and the unemployment rate, along with exchange rates for commodity currencies, and indicators of global economic activity.

Second, how does commodity price predictability vary with the forecast horizon? To address this question, we consider the monthly, quarterly, and annual horizons separately. Bottlenecks between the demand and supply of different types of commodities can be important in the short run, but we would expect them to be resolved in the longer run, and so the evidence of predictability may well depend on the forecast horizon.

Third, does commodity price predictability depend on the underlying economic state? The evidence from stock markets presented by Henkel, Martin, and Nardari (2011) and Rapach, Strauss, and Zhou (2010) suggests that the predictability of stock returns is largely confined to economic recessions. Clearly, it is of interest to see whether a similar finding carries over to commodity markets, in which the state of the economy would be expected to play an important role. We address this question by considering the strength of the predictive evidence during recessions and expansions separately.

Fourth, does the predictability of commodity prices vary across different types of commodities, such as agricultural versus raw industrial commodities? Findings of such differences are of interest, since they could be indicative of the types of storage costs and convenience yields that are affected by macroeconomic conditions.

Empirically, we find that the strength of the evidence on commodity price predictability is linked to the length of the forecast horizon. For example, the two commodity currencies possess strong predictive power at the monthly and quarterly horizons, but not at the annual horizon. In contrast, growth in industrial production has some predictive power in annual forecasts. One other variable, the investment–capital ratio, also comes out as having predictive power in the quarterly and annual regressions. Overall, the out-of-sample evidence on the predictability of commodity prices is strongest at the quarterly horizon.

We also find evidence that the predictability of commodity prices is strongest in recessions and largely absent in expansions. Specifically, the unemployment rate, changes in the two commodity currencies, the term spread, and the investment–capital ratio are capable of predicting commodity price movements with higher levels of accuracy in recessions than in expansions, in a way that is statistically significant.

A decomposition of this result suggests that many predictor variables become more volatile during recessions, but also that their slope coefficients in predictive regressions increase in recessions. This dominates the concomitant increase in the volatility of the residuals of the predictive regressions during recessions.

Return predictability appears to vary considerably across different types of commodities. There is some evidence of out-of-sample predictability of movements in metals and raw industrials commodity spot price indexes, as well as for the aggregate commodity spot price index. In contrast, there is very little evidence suggesting that movements in the prices of fats and oils, foods, or livestock are predictable.

Finally, we find that multivariate regressions that adjust for the effects of estimation error on the forecasts through either shrinkage (ridge regression) or model combination (complete subset regressions) produce reasonably good out-of-sample forecasts, particularly for the metals, industrials, and aggregate commodity price indexes.

The outline of the paper is as follows. Section 2 introduces the data. Section 3 presents empirical results for the univariate models which are used to capture the predictability of movements in commodity spot prices associated with individual predictor variables. Section 4 explores predictability using multivariate predictability models, Section 5 considers variations in commodity price predictability across recessions and expansions, and Section 6 concludes.

## 2. Data

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

As predictors, we consider a set of 16 state variables. The first seven variables are from the literature on stock return predictability, and were 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; *Treasury 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; *investment to capital ratio  ik)* is the ratio of aggregate investments to aggregate capital for the whole economy; and *inflation  infl)* is the (log) growth in the consumer price index (all urban consumers). These series were constructed by Goyal and Welch (2008), and are available on the authors' website.

The second set of variables aims to measure the broad state of the economy. Specifically, we use the following macro variables. First, *industrial production growth* (  IND), the monthly growth in industrial production, as reported by the Archival Federal Reserve Bank of St. Louis (ALFRED mnemonic: INDPRO). Quarterly and annual series are obtained by averaging monthly values over each quarter and year. For example, letting $\mathrm{IND}_{Y2:M2}$ and $\mathrm{IND}_{Y2:Q2}$ 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:

$$\mathrm{IND}_{Y2:M2} = \ln(\mathrm{IND}_{Y2:M2}) \quad \ln(\mathrm{IND}_{Y2:M1})$$

$$\mathrm{IND}_{Y2:Q2} = \ln \left. \sum_{j=4}^{6} \mathrm{IND}_{Y2:Mj} \right) \quad \ln \left. \sum_{i=1}^{3} \mathrm{IND}_{Y2:Mi} \right) \qquad (1)$$

$$\mathrm{IND}_{Y2} = \ln \left. \sum_{j=1}^{12} \mathrm{IND}_{Y2:Mj} \right) \quad \ln \left. \sum_{i=1}^{12} \mathrm{IND}_{Y1:Mi} \right).$$

Second, *money stock* (  $M1$), the log growth in the monthly M1 money stock (Philadelphia FED mnemonic: m1), with the quarterly and annual series again obtained by averaging monthly values over each quarter and year. Monthly, quarterly and annual growth rates are computed as for industrial production. Third, *GDP growth* (  GDP), the log growth in the annual GDP (Philadelphia FED mnemonic: routput). Finally, *unemployment* (UN), the monthly unemployment rate (ALFRED mnemonic: UNRATE); quarterly and annual series are obtained by averaging the monthly values over each quarter and year, respectively.

Many macroeconomic variables are revised regularly due to government agencies' use of preliminary data. For example, some components of GDP do not become available until some months after the initial release. Occasionally, major revisions affect the methodology used to construct the data (e.g., fixed- or chain-weighting); see Croushore and Stark (2001) for a further discussion of this point. Because of such revisions, the initially released series might be less accurate than data that are subsequently revised. In order to circumvent any bias which may be introduced by using ex-post revised data, we use vintage series to estimate the models. This ensures that, at any point in time, our forecasts are based only on data which were available at the time of the forecast. In order to account for publication cycles, we also lag some predictors by an extra period, using two-month lags rather than one-month lagged values for GDP, M1 money stock and industrial production.

Fluctuations in commodity prices have been linked to demand pressures from emerging economies, especially China and India. To track the demand for industrial commodities in global markets, we use Kilian's real economic activity index (Kilian, 2009).[4] Because commodities are traded globally, we also include two commodity currencies (Chen et al., 2010), namely the log first difference of the Australian dollar–US dollar (Global Financial Database mnemonic: USDAUD) and the Indian rupee–US dollar (Global Financial Database mnemonic: USDINR) exchange rates. These two countries are among the largest exporters of industrial and agricultural commodities, respectively.

Finally, to capture information from financial derivatives markets, we include the S&P Goldman Sachs Commodity Index®, a composite index of commodity sector returns representing an unleveraged, long-only investment in commodity futures that is broadly diversified across a spectrum of commodities (Datastream mnemonic: GSCITOT).[5] Hong and Yogo (2012) show that the futures market open interest (the total number of futures contracts written on a given commodity) is a better proxy of future expected prices, so we also include the futures market open interest of industrial and metal commodities as a predictor.[6]

3 For further details, see http://www.crbtrader.com/crbindex/spot_background.asp.

4 This is available on Kilian's website, http://www-personal.umich.edu/lkilian/reaupdate.txt.

5 See Alquist and Kilian (2010) for evidence on the predictability of oil prices from the oil futures spread.

6 This is available on Yogo's web page, https://sites.google.com/site/motohiroyogo/home/research.

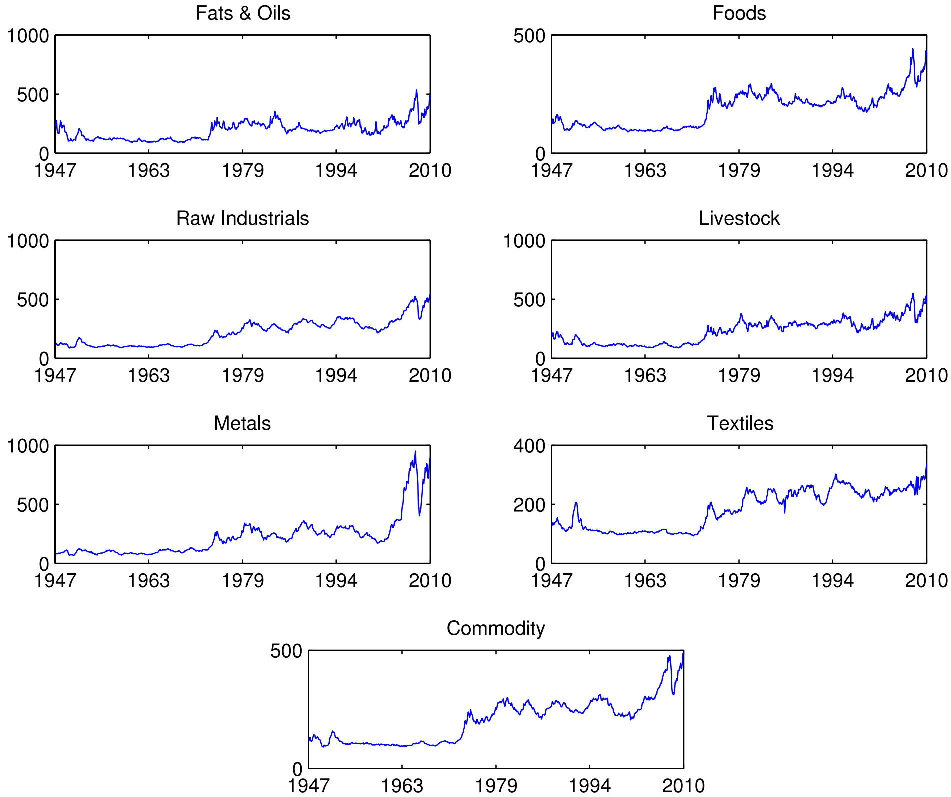


**Fig. 1.** *Commodity prices.* This figure plots monthly values of the Reuters/Jeffries-CRB spot price indexes compiled by the Commodity Research Bureau. Prices are measured in nominal US dollar terms. The indexes are based on 22 individual commodities, including raw industrials (burlap, copper scrap,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

### 2.3. *Data characteristics*

Fig. 1 presents plots of the nominal commodity spot prices for the seven indexes. Many of the indexes underwent sharp increases in 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 the exception of textiles) during the global financial crisis. Between March 2009 and the end of our sample (2010), commodity prices recovered sharply.

Fig. 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 $t+1$ are 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 levels of 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 a comparison, we also show results for 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.

The volatility varied a great deal across commodities, being lowest for industrials, at 2.84% per month, which was less than half the level observed for fats and oils (6.61%). All of the commodity returns were more volatile than the bond returns, while three of the indexes (fats 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 those 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 of around 0.3 at the monthly horizon. This serial correlation is only mildly reduced at the quarterly horizon, but disappears in the annual data.[7]

[7] 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.

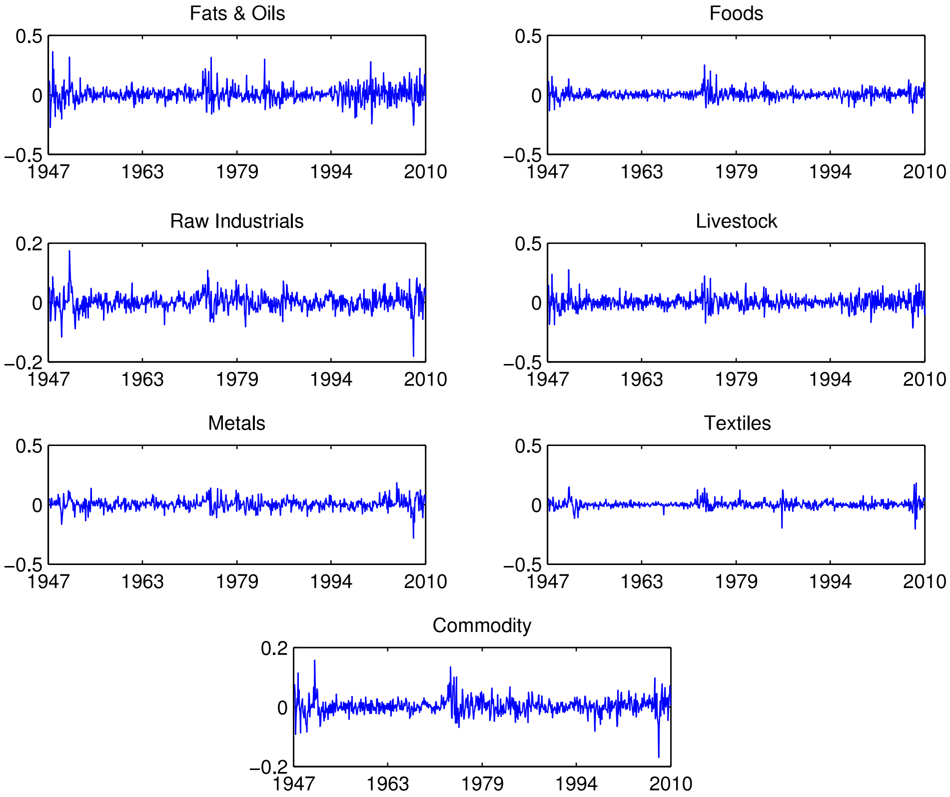


**Fig. 2.** *Commodity returns.* This figure plots monthly returns on the Reuters/Jeffries-CRB spot price indexes compiled by the Commodity Research Bureau. Prices are measured in nominal US dollar terms.

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

## 3. Empirical results

Following studies on stock return predictability, such as those of Goyal and Welch (2008) and Rapach et al. (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:

$$r_{t+1:t+h} \equiv \frac{P_{t+h} - P_t}{P_t} = \beta_{0h} + \beta_{1h} x_t + \varepsilon_{t+1:t+h}, \qquad (2)$$

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 predictor variable.

### 3.1. In-sample return predictability

Pairing each of the commodity price series with each of the individual predictor variables in turn, Table 2 reports in-sample estimates of the slope coefficients obtained from Eq. (2). 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, many predictors, such as the default return spread, growth in industrial production, the two commodity currencies, open interest and the Goldman Sachs futures index, have broad predictive power over the majority of commodity price indexes considered here. In addition, variables such as the long-term return, the unemployment rate, and the real activity measure have predictive power over some of the individual indexes. Predictability is strongest for industrials, metals, textiles, and the broad commodity price index, and weakest for fats/oils, foods, and livestock.[8]

In-sample predictability is a bit weaker at the quarterly horizon, although a number of variables still appear to

[8] Commodity returns have non-Gaussian properties, such as heteroscedasticity, skewness, and fat tails. Therefore, to evaluate the statistical significance of our results, we compute $p$-values using the wild bootstrap. Specifically, we repeat the following procedure 5000 times.

1. Resample pairs of $(\hat{\varepsilon}, \hat{\eta})$ with replacement from OLS residuals in the regressions $r_{t+1} = \alpha + \varepsilon_{t+1}$ and $x_{t+1} = \mu + \rho x_t + \eta_{t+1}$, and multiply them by a random variable $\nu_i$, which follows the Rademacher distribution: $\nu_i = 1$ with probability 0.5, and $\nu_i = -1$ with probability 0.5. Denote these residuals by $(\tilde{\varepsilon}, \tilde{\eta})$.
2. Build time series of predictors, $x_t$, by initially drawing from the unconditional mean $\hat{\mu}/(1-\hat{\rho})$, then iterating forward on the $x_{t+1}$ equation using the OLS estimates $\hat{\mu}$ and $\hat{\rho}$, and the resampled residual $\tilde{\eta}_{t+1}$.

**Table 1**
Summary statistics for commodity returns.

| | Fats & oils | Foods | Industrials | Livestock | Metals | Textiles | Commodity | Stock | Bond |
|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Monthly* | | | | | | | | | |
| 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* | | | | | | | | | |
| 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* | | | | | | | | | |
| 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 | – | 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 | – |

This table reports the mean, standard deviation, coefficient of skew, coefficient of kurtosis, and 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 the correlations between monthly return series above the diagonal and those between annual returns below the diagonal.

possess predictive power over commodity prices. Specifically, the inflation rate, growth in industrial production, open interest in metals, and the two commodity currency series have strong power over commodity prices at this horizon. Again, predictability is strongest for industrials, metals, textiles, and the broad commodity price index.

At the annual horizon, the evidence of in-sample commodity price predictability is reduced still further. The investment–capital ratio, the inflation rate, and open interest for industrials continue to have significant predictive power over more than half of the indexes, however, with the evidence being strongest for the industrials and metals price indexes.

3. Construct time series of returns, $r_t$, by adding the resampled residual $\tilde{\varepsilon}_{t+1}$ to the sample mean (under the null that returns are not predictable).
4. Use the resulting $x_t$ and $r_t$ series to estimate return regressions by OLS.

The bootstrapped $p$-values associated with the reported $\beta$-values are the relative frequency with which the (absolute value) of the bootstrapped $t$-statistics in point 4 exceeds the actual value.

These results suggest that a range of macroeconomic and financial variables do have predictive power over some commodity price indexes, though only the open interest variables seem to generate consistent predictability across the three horizons considered here. However, other individual predictors seem capable of predicting commodity price movements at some, but not all, horizons. Interestingly, the least successful among the predictor variables considered here are perhaps the predictors which are traditionally considered in the literature on the predictability of stock and bond returns. Conversely, the best predictors of commodity returns do not generally generate much predictability for stock and bond returns.

### 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 by using

**Table 2**
Coefficient estimates for univariate prediction models.

| | 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 |
| CPI | 1.065$^{*}$ | 0.458 | 0.522$^{**}$ | 0.551 | 0.517 | 0.012 | 0.493$^{**}$ | 0.656 | 0.262 |
| INDPRO | 0.242 | 0.189 | 0.575$^{***}$ | 0.261 | 0.748$^{***}$ | 0.356$^{***}$ | 0.414$^{***}$ | 0.063 | 0.136$^{*}$ |
| M1 | 0.504 | 0.193 | 0.084 | 0.223 | 0.003 | 0.618$^{***}$ | 0.056 | 0.250 | 0.199 |
| UNRATE | 0.001 | 0.000 | 0.001$^{***}$ | 0.001 | 0.001 | 0.001$^{***}$ | 0.001$^{*}$ | 0.002$^{***}$ | 0.001$^{***}$ |
| USDAUS | 0.188$^{**}$ | 0.080 | 0.197$^{***}$ | 0.171$^{**}$ | 0.227$^{***}$ | 0.183$^{***}$ | 0.149$^{***}$ | 0.011 | 0.169$^{***}$ |
| USDINR | 0.174 | 0.079 | 0.187$^{***}$ | 0.187$^{*}$ | 0.254$^{***}$ | 0.136$^{**}$ | 0.161$^{***}$ | 0.024 | 0.130$^{***}$ |
| Real activity | 1.839 | 1.894$^{***}$ | 3.475 | 3.581 | 1.172 | 2.328 | 9.527$^{**}$ | 1.098 | 3.489 |
| Open interest ind | 0.107$^{***}$ | 0.054$^{**}$ | 0.064$^{***}$ | 0.100$^{***}$ | 0.072$^{***}$ | 0.042$^{***}$ | 0.061$^{***}$ | 0.004 | 0.034$^{**}$ |
| Open interest met | 0.040 | 0.034$^{*}$ | 0.041$^{***}$ | 0.029 | 0.056$^{***}$ | 0.028$^{**}$ | 0.038$^{***}$ | 0.003 | 0.013 |
| GSCI | 0.217$^{***}$ | 0.109$^{***}$ | 0.077$^{***}$ | 0.190$^{***}$ | 0.082$^{**}$ | 0.013 | 0.093$^{***}$ | 0.048 | 0.051$^{***}$ |
| 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 |
| CPI | 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 |
| INDPRO | 0.506 | 0.307 | 0.643$^{***}$ | 0.354 | 0.662$^{**}$ | 0.380$^{**}$ | 0.503$^{***}$ | 0.215 | 0.076 |
| M1 | 0.438 | 0.181 | 0.805$^{**}$ | 0.657 | 1.008$^{**}$ | 0.604$^{*}$ | 0.551$^{*}$ | 0.116 | 0.109 |
| UNRATE | 0.002 | 6.287 | 0.005$^{**}$ | 0.004 | 0.004 | 0.005$^{**}$ | 0.003 | 0.007$^{**}$ | 0.003$^{**}$ |
| USDAUS | 0.401$^{***}$ | 0.290$^{***}$ | 0.375$^{***}$ | 0.468$^{***}$ | 0.478$^{***}$ | 0.191$^{***}$ | 0.323$^{***}$ | 0.000 | 0.198$^{***}$ |
| USDINR | 0.297$^{*}$ | 0.254$^{**}$ | 0.230$^{**}$ | 0.417$^{***}$ | 0.184 | 0.227$^{***}$ | 0.238$^{***}$ | 0.211$^{*}$ | 0.155$^{**}$ |
| Real activity | 4.347 | 4.426$^{**}$ | 2.594 | 2.437 | 3.260 | 3.726 | 1.905 | 5.052$^{**}$ | 5.971 |
| Open interest ind | 0.177$^{***}$ | 0.045 | 0.087$^{***}$ | 0.091$^{*}$ | 0.107$^{**}$ | 0.046 | 0.071$^{**}$ | 0.032 | 0.053$^{**}$ |
| Open interest met | 0.159$^{**}$ | 0.095$^{**}$ | 0.115$^{***}$ | 0.072 | 0.132$^{**}$ | 0.094$^{***}$ | 0.106$^{***}$ | 0.021 | 0.037 |
| GSCI | 0.062 | 0.033 | 0.042 | 0.001 | 0.016 | 0.025 | 0.037 | 0.056 | 0.003 |
| 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 |
| CPI | 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 |
| INDPRO | 0.655 | 0.300 | 1.204$^{**}$ | 0.762 | 0.846 | 0.913$^{**}$ | 0.569 | 0.301 | 0.229 |
| M1 | 0.496 | 0.669 | 0.862 | 0.670 | 1.383 | 0.554 | 0.794 | 0.603 | 0.197 |
| UNRATE | 0.016 | 0.003 | 0.030$^{*}$ | 0.018 | 0.032 | 0.023$^{*}$ | 0.019 | 0.011 | 0.014$^{*}$ |
| GDP | 1.744 | 0.493 | 2.289$^{**}$ | 1.806$^{*}$ | 1.412 | 1.714$^{**}$ | 1.108 | 0.852 | 0.253 |
| USDAUS | 0.362 | 0.046 | 0.476$^{**}$ | 0.311 | 0.368 | 0.336$^{*}$ | 0.234 | 0.270 | 0.059 |
| USDINR | 0.389 | 0.100 | 0.471$^{**}$ | 0.328 | 0.525 | 0.299 | 0.291 | 0.377$^{*}$ | 0.002 |
| Real activity | 2.805 | 3.914 | 2.061$^{**}$ | 2.007$^{**}$ | 2.499 | 1.177 | 1.032 | 2.044$^{**}$ | 4.378 |
| Open interest ind | 0.310$^{**}$ | 0.178$^{*}$ | 0.327$^{***}$ | 0.077 | 0.472$^{***}$ | 0.311$^{***}$ | 0.259$^{***}$ | 0.093 | 0.091 |
| Open interest met | 0.195 | 0.081 | 0.305$^{***}$ | 0.092 | 0.593$^{***}$ | 0.144$^{*}$ | 0.211$^{***}$ | 0.023 | 0.157$^{**}$ |
| GSCI | 0.018 | 0.044 | 0.171 | 0.164$^{*}$ | 0.336$^{*}$ | 0.024 | 0.076 | 0.114 | 0.006 |
| AR(1) | 0.075 | 0.135 | 0.128 | 0.119 | 0.128 | 0.073 | 0.008 | 0.049 | 0.094 |

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 the predictor. All of the 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 ( CPI), the investment–capital ratio (ik), growth in industrial production ( IND), money supply growth ( M1), the unemployment rate (UNRATE), GDP growth ( GDP), change in the exchange rate of the US dollar to the Australian dollar ( USDAUD) and the Indian rupee ( USDINR), the real activity index of Kilian (2009), the futures market open interest of industrial (Open Interest Ind) and metal (Open Interest Met) commodities, the return on the Goldman Sachs Commodity Index (GSCI) and the one-period lagged return (AR(1)). $p$-values are computed using a bootstrap.

$^{***}$ Indicates statistical significance at the 1% level.
$^{**}$ Indicates statistical significance at the 5% level.
$^{*}$ Indicates statistical significance at the 10% level.

**Table 3a**
Out-of-sample forecast performance: univariate prediction models, 1971–2010.

| | *Panel A: Monthly* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Fats/oils | Foods | Industrials | Livestock | Metals | Textiles | Commodity | Stock | Bond |
| dp | 1.010 | 1.012 | 1.019$^{*}$ | 1.011 | 1.013 | 1.010 | 1.014 | 1.005 | 0.996$^{**}$ |
| tbl | 1.009 | 1.007 | 1.005 | 1.009 | 1.004 | 1.009 | 1.006 | 1.007 | 0.999$^{*}$ |
| ltr | 0.999$^{*}$ | 1.002 | 0.983$^{***}$ | 1.001 | 0.985$^{***}$ | 0993$^{*}$ | 0.991$^{***}$ | 1.000 | 1.006 |
| tms | 1.008 | 1.010 | 1.003 | 1.008 | 1.012 | 1.005 | 1.008 | 1.001 | 1.006 |
| dfr | 1.010 | 1.013 | 0.981$^{**}$ | 0.988$^{*}$ | 0.978$^{**}$ | 1.009 | 1.001 | 1.025 | 1.010 |
| CPI | 1.001 | 1.003 | 1.015 | 1.006 | 1.024 | 1.000 | 1.009 | 1.002 | 1.003 |
| INDPRO | 1.009 | 1.011 | 0.998 | 1.016 | 1.002 | 1.000 | 1.004 | 1.004 | 0.985$^{**}$ |
| M1 | 1.011 | 1.012 | 1.013 | 1.025 | 1.009 | 0.999 | 1.013 | 1.005 | 1.018 |
| UNRATE | 1.010 | 1.009 | 0.993$^{*}$ | 1.008 | 1.002 | 1.004 | 1.001 | 1.004 | 0.996 |
| USDAUS | 0.997 | 1.010 | 0.973$^{***}$ | 1.017 | 0.990$^{**}$ | 0.991$^{**}$ | 0.982$^{***}$ | 1.005 | 0.953$^{***}$ |
| USDINR | 1.005 | 1.010 | 0.990$^{*}$ | 1.003 | 0.994 | 1.017 | 0.990$^{*}$ | 1.005 | 0.994$^{**}$ |
| AR(1) | 1.003 | 1.002 | 0.896$^{***}$ | 0.992$^{**}$ | 0.920$^{***}$ | 1.009 | 0.943$^{***}$ | 1.008 | 1.004 |
| | *Panel B: Quarterly* | | | | | | | | |
| | Fats/oils | Foods | Industrials | Livestock | Metals | Textiles | Commodity | Stock | Bond |
| dp | 1.034 | 1.032 | 1.049 | 1.045 | 1.033 | 1.038 | 1.038 | 1.005 | 1.002 |
| tbl | 1.025 | 1.011 | 1.021 | 1.023 | 1.016 | 1.030 | 1.009 | 1.022 | 0.995$^{*}$ |
| ltr | 1.025 | 1.022 | 1.033 | 1.022 | 1.038 | 1.010 | 1.026 | 1.003 | 1.053 |
| tms | 1.021 | 1.032 | 1.019 | 1.035 | 1.038 | 1.014 | 1.020 | 1.015 | 1.030 |
| dfr | 1.041 | 1.031 | 0.994 | 1.046 | 0.993 | 1.025 | 1.011 | 1.032 | 1.031 |
| CPI | 0.961$^{*}$ | 1.013 | 0.964 | 0.956$^{*}$ | 0.986 | 1.035 | 0.970 | 1.020 | 1.002 |
| ik | 0.996 | 0.983$^{**}$ | 0.953$^{***}$ | 1.003 | 0.965$^{**}$ | 0.988$^{*}$ | 0.957$^{***}$ | 0.997 | 1.022 |
| INDPRO | 1.031 | 1.017 | 1.045 | 1.042 | 1.043 | 1.010 | 1.041 | 1.025 | 1.023 |
| M1 | 1.029 | 1.014 | 0.939$^{***}$ | 1.024 | 0.957$^{**}$ | 0.996$^{*}$ | 0.985$^{**}$ | 1.043 | 1.025 |
| UNRATE | 1.026 | 1.026 | 0.983$^{*}$ | 1.018 | 1.003 | 0.985$^{**}$ | 1.000 | 1.008 | 0.998 |
| USDAUS | 1.059 | 1.023 | 0.986$^{***}$ | 0.985$^{***}$ | 1.004 | 1.062 | 0.970$^{**}$ | 1.048 | 0.974$^{**}$ |
| USDINR | 0.971$^{**}$ | 0.965$^{***}$ | 0.972$^{**}$ | 0.944$^{***}$ | 0.995 | 0.978$^{**}$ | 0.952$^{***}$ | 1.006 | 0.961$^{***}$ |
| AR(1) | 1.026 | 1.035 | 0.971$^{***}$ | 1.020 | 1.014 | 1.007 | 0.994$^{**}$ | 1.007 | 1.037 |
| | *Panel C: Annual* | | | | | | | | |
| | Fats/oils | Foods | Industrials | Livestock | Metals | Textiles | Commodity | Stock | Bond |
| dp | 1.183 | 1.122 | 1.137 | 1.166 | 1.117 | 1.166 | 1.136 | 0.970$^{**}$ | 1.059 |
| tbl | 1.037 | 1.015 | 0.936$^{*}$ | 0.962$^{*}$ | 0.855$^{**}$ | 1.100 | 0.935$^{**}$ | 1.107 | 0.995$^{***}$ |
| ltr | 1.080 | 1.032 | 1.001 | 1.103 | 1.034 | 1.036 | 1.035 | 1.102 | 1.021 |
| tms | 1.032 | 1.079 | 0.955$^{**}$ | 1.074 | 0.962$^{**}$ | 1.056 | 0.993$^{*}$ | 1.054 | 1.023 |
| dfr | 1.085 | 1.055 | 1.252 | 1.208 | 1.313 | 1.101 | 1.189 | 1.137 | 1.095 |
| CPI | 1.026 | 1.166 | 0.964 | 1.041 | 0.866$^{*}$ | 1.146 | 1.001 | 1.161 | 1.013 |
| ik | 0.942$^{**}$ | 0.966$^{*}$ | 0.926$^{**}$ | 1.009 | 0.914$^{**}$ | 1.030 | 0.924$^{***}$ | 1.010 | 1.113 |
| INDPRO | 0.935$^{*}$ | 0.940$^{**}$ | 0.941$^{**}$ | 0.876$^{*}$ | 1.006 | 0.965$^{*}$ | 0.936$^{*}$ | 1.124 | 1.114 |
| M1 | 1.129 | 1.104 | 1.099 | 1.194 | 1.089 | 1.122 | 1.092 | 1.192 | 1.040 |
| UNRATE | 1.073 | 1.022 | 1.084 | 1.040 | 1.074 | 1.084 | 1.068 | 0.917$^{*}$ | 1.035 |
| GDP | 0.922$^{*}$ | 0.898$^{**}$ | 1.001 | 0.907$^{*}$ | 1.036 | 1.018 | 0.965$^{*}$ | 1.004 | 1.081 |
| USDAUS | 1.559 | 1.456 | 1.991 | 1.823 | 1.608 | 1.102 | 1.776 | 1.145 | 1.085 |
| USDINR | 1.043 | 1.026 | 1.025 | 1.041 | 1.061 | 1.004 | 1.031 | 1.026 | 1.288 |
| AR(1) | 1.050 | 1.110 | 1.197 | 1.146 | 1.139 | 1.654 | 1.435 | 1.175 | 1.065 |

This table reports the ratio of the mean squared forecast error of the univariate return prediction models that include a constant and the predictor variable listed in each row, to the mean squared forecast error of the benchmark model which assumes no predictability, $MSFE_{Univar}/MSFE_{Bench}$. The forecast evaluation period is 1971–2010. All of the forecasts are updated recursively, using a 20-year rolling estimation window. Commodity returns are based on the Reuters/Jeffries CRB spot price indexes. Values smaller than one indicate that the univariate model performs better than the benchmark. The statistical significance of the null of equal predictive ability is measured using the Clark and West (2007) test.

$^{***}$ Indicates statistical significance at the 1% level.

$^{**}$ Indicates statistical significance at the 5% level.

$^{*}$ Indicates statistical significance at the 10% level.

recursively estimated parameter values to generate forecasts. We follow this procedure and use a rolling window estimator with a window size ($v$) of 20 years' worth of observations. Specifically, setting $z_t = (1\ x_t)'$, forecasts are generated as $\hat{r}_{t+1|t} = \hat{\beta}_t' z_t$, where

$$\hat{\beta}_t = \left(\sum_{\tau=t-v+1}^{t} z_{\tau-1} z_{\tau-1}'\right)^{-1} \left(\sum_{\tau=t-v+1}^{t} z_{\tau-1} r_{\tau}\right)$$

is the least squares estimate. We start our out-of-sample forecasts in 1971, so the evaluation period is 1971:01–2010:12. Some variables, such as the GSCI commodity futures prices index and the open interest series, do not have sufficiently long data records to be used in the out-of-sample experiments, so they are dropped from this part of the analysis.

For each of the univariate models, Table 3a reports out-of-sample mean squared error (MSE) values, measured relative to the MSE obtained from the prevailing mean benchmark model that only includes a constant, and so sets $\beta_{1h} = 0$ in Eq. (2). Values of this ratio of more than one suggest that a given model performs worse than the benchmark, while values below one suggest the opposite.

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 and 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:

$$\mathrm{MSE}^{\mathrm{adj}} = P^{-1}\sum_{t=R}^{T-1} \bar{e}^2_{t+1|t} - P^{-1}\sum_{t=R}^{T-1} \hat{e}^2_{t+1|t} + P^{-1}\sum_{t=R}^{T-1} (\bar{r}_{t+1|t} - \hat{r}_{t+1|t})^2. \quad (3)$$

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, $\bar{r}_{t+1|t}$ 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 Eq. (3) adjusts for the typically higher variability associated with the forecasts generated by the larger (univariate) model, relative to the prevailing mean forecast.

First, consider the monthly results in Panel A. Many of the MSE-ratio values exceed one, as a result of the effect of parameter estimation error, which reduces the precision of the forecasts, see Clark and West (2007) and Inoue and Killian (2008). However, for some of the predictor variables – notably, the long-term return, lagged returns, and the US–Australian dollar exchange rate – we find MSE values that are significantly below unity, with improvements in predictive accuracy of between one and three percent. Compared with the in-sample evidence, the out-of-sample results are clearly weaker, though. There is essentially little or no evidence of predictability for the fats/oils, foods, livestock, and textiles indexes, while the evidence is strongest for industrials, metals and the total commodity price index.

Out-of-sample predictability is stronger at the quarterly horizon (Panel B). At this horizon, the investment–capital ratio, along with the two commodity currencies and growth in the money supply, produce significantly more accurate predictions than the benchmark. Again, the evidence is strongest for industrials, followed by the total commodity price index, textiles, and metals.

Finally, turning to the annual horizon, the investment–capital ratio and growth in industrial production produce the strongest statistical evidence that they can help improve the forecast precision relative to the prevailing mean benchmark, while the T-bill rate and GDP growth have weaker predictive power for some of the indexes. Interestingly, there is no evidence at this horizon that the commodity currencies improve forecasts, nor do lagged returns help.

### 3.3. Sub-sample results

Table 3a showed the results for the full evaluation sample, 1971–2010. There is plenty of evidence of instability in the predictability of asset prices, so it is worth analyzing whether commodity prices were more or less predictable in different subsamples. To this end, we split the sample in two, retaining 1971–1990 as the first half and 1991–2010 as the second half. Tables 3b and 3c show the evidence from this analysis. During the first subsample, the long-term return, the growth in industrial production and lagged returns are all significant for many of the commodity price series at the monthly horizon. At the quarterly horizon, money growth and the two commodity currencies possess predictive power over a range of commodity price indexes. Finally, at the annual horizon, few predictors seem capable of improving on the benchmark's commodity price forecasts.

Turning to the second subsample, 1991–2010, only the commodity currencies lead to notable improvements for the monthly forecasts. At the quarterly horizon, the investment–capital ratio continues to do well, as does the US dollar–Indian rupee exchange rate. The investment–capital ratio, the term spread, and the growth in industrial production continue to better the annual forecasts relative to the benchmark.

An alternative way to inspect the evolution of return predictability over time is to examine the cumulated sum of squared error differential between the benchmark model and a candidate prediction model proposed by Goyal and Welch (2008):

$$\mathrm{SSE}_t = \sum_{\tau=1}^{t} e^2_\tau(\mathrm{Bmk}) - \sum_{\tau=1}^{t} e^2_\tau(\mathrm{Model}). \quad (4)$$

Positive values of this measure indicate that the candidate forecasting model produced more accurate forecasts than the benchmark up to that point in time. Periods associated with an increase in SSE suggest that the particular forecasting model produced a lower MSE value than the benchmark, while, conversely, declines in SSE suggest that the forecasts were less precise than those based on the benchmark. Hence, plots of SSE provide a useful diagnostic that helps identify periods of (relative) out- or under-performance.

Fig. 3 provides such plots for the quarterly total commodity price index series, using each of the individual predictors included in our study. Confirming the impressions from Table 3, the predictor variables identified in the literature on stock return predictability have essentially no power over commodity price movements. The same holds for the inflation rate ( CPI) right up to the financial crisis of 2008/2009, after which this predictor does very well. The figures suggest that the only variables which consistently produce accurate forecasts of the aggregate commodity price index throughout the entire sample 1971–2010 are the investment–capital ratio and the US dollar–Indian rupee exchange rate.

**Table 3b**
Out-of-sample forecast performance: univariate prediction models, 1971–1990.

| | Panel A: Monthly | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Fats/oils | Foods | Industrials | Livestock | Metals | Textiles | Commodity | Stock | Bond |
| dp | 1.011 | 1.014 | 1.005 | 1.015 | 0.997$^{**}$ | 1.002 | 1.006 | 1.002 | 0.983$^{**}$ |
| tbl | 1.011 | 1.005 | 0.994 | 1.007 | 1.007 | 1.004 | 0.996 | 1.012 | 0.991$^{*}$ |
| ltr | 0.989$^{**}$ | 1.001 | 0.958$^{***}$ | 0.990$^{*}$ | 0.959$^{***}$ | 0.993$^{**}$ | 0.966$^{***}$ | 0.997$^{*}$ | 1.007 |
| tms | 1.011 | 1.011 | 1.007 | 1.013 | 1.021 | 1.011 | 1.009 | 0.998$^{**}$ | 1.006 |
| dfr | 1.006 | 1.003 | 0.988$^{*}$ | 0.995 | 0.986$^{**}$ | 1.000 | 0.996 | 1.010 | 1.006 |
| CPI | 1.009 | 1.008 | 1.014 | 1.019 | 1.017 | 1.008 | 1.013 | 0.990 | 1.008 |
| INDPRO | 0.998 | 1.012 | 0.984$^{**}$ | 1.011 | 0.988$^{*}$ | 0.993$^{**}$ | 0.995 | 1.001 | 0.968$^{***}$ |
| M1 | 1.012 | 1.011 | 1.017 | 1.031 | 1.010 | 1.009 | 1.011 | 1.015 | 1.015 |
| UNrate | 1.011 | 1.012 | 1.005 | 1.009 | 1.010 | 1.002 | 1.008 | 1.005 | 0.991 |
| USDAUS | 1.013 | 1.021 | 1.003 | 1.068 | 1.017 | 0.968$^{**}$ | 1.006 | 1.005 | 0.947$^{***}$ |
| USDINR | 1.023 | 1.022 | 1.035 | 1.020 | 1.028 | 1.049 | 1.029 | 1.008 | 1.002 |
| AR(1) | 1.010 | 0.996 | 0.886$^{***}$ | 0.988$^{*}$ | 0.905$^{***}$ | 1.006 | 0.933$^{***}$ | 1.010 | 1.005 |
| | Panel B: Quarterly | | | | | | | | |
| | Fats/oils | Foods | Industrials | Livestock | Metals | Textiles | Commodity | Stock | Bond |
| dp | 1.031 | 1.039 | 1.031 | 1.066 | 1.002 | 1.027 | 1.021 | 0.999$^{*}$ | 0.968$^{*}$ |
| tbl | 1.016 | 0.999 | 1.013 | 1.013 | 1.037 | 1.028 | 0.981$^{*}$ | 1.035 | 0.977$^{*}$ |
| ltr | 1.022 | 1.032 | 1.033 | 1.019 | 1.049 | 0.991$^{**}$ | 1.020 | 0.998 | 1.065 |
| tms | 1.030 | 1.039 | 1.041 | 1.071 | 1.070 | 1.031 | 1.029 | 1.010 | 1.037 |
| dfr | 0.995 | 1.007 | 1.000 | 1.018 | 1.002 | 1.024 | 0.996 | 0.993$^{*}$ | 1.022 |
| CPI | 1.027 | 1.028 | 1.045 | 1.032 | 1.059 | 1.049 | 1.031 | 1.039 | 1.016 |
| ik | 0.994 | 0.974$^{*}$ | 1.003 | 0.995 | 1.016 | 1.003 | 0.989 | 0.970$^{*}$ | 1.014 |
| INDPRO | 1.008 | 1.023 | 0.992 | 1.011 | 0.994 | 0.999 | 1.006 | 0.984 | 1.004 |
| M1 | 1.035 | 1.018 | 0.935$^{***}$ | 1.030 | 0.960$^{**}$ | 0.979$^{*}$ | 0.978$^{**}$ | 1.049 | 1.021 |
| UNrate | 1.044 | 1.043 | 1.003 | 1.037 | 1.017 | 1.001 | 1.024 | 1.014 | 0.990 |
| USDAUS | 1.101 | 1.039 | 1.025 | 0.943$^{***}$ | 1.029 | 1.091 | 0.966$^{**}$ | 1.043 | 0.924$^{**}$ |
| USDINR | 0.983$^{*}$ | 0.964$^{**}$ | 0.993 | 0.942$^{***}$ | 1.007 | 0.979$^{*}$ | 0.968$^{**}$ | 1.002 | 0.995 |
| AR(1) | 1.043 | 1.035 | 0.994$^{*}$ | 1.024 | 1.047 | 1.027 | 0.993$^{*}$ | 1.001 | 1.047 |
| | Panel C: Annual | | | | | | | | |
| | Fats/oils | Foods | Industrials | Livestock | Metals | Textiles | Commodity | Stock | Bond |
| dp | 1.196 | 1.094 | 1.126 | 1.206 | 1.080 | 1.146 | 1.121 | 0.897$^{**}$ | 0.978 |
| tbl | 1.046 | 1.002 | 0.976 | 0.983 | 0.911$^{*}$ | 1.122 | 0.949$^{*}$ | 1.144 | 0.937$^{***}$ |
| ltr | 1.067 | 1.054 | 0.925$^{**}$ | 1.105 | 1.011 | 0.987$^{*}$ | 0.991 | 1.163 | 1.091 |
| tms | 1.048 | 1.077 | 1.021 | 1.250 | 0.997$^{*}$ | 1.126 | 1.045 | 1.070 | 1.005 |
| dfr | 0.986$^{*}$ | 1.003 | 1.037 | 1.079 | 1.061 | 1.032 | 1.022 | 0.944 | 1.096 |
| CPI | 1.088 | 1.240 | 1.082 | 1.266 | 0.972 | 1.214 | 1.091 | 1.294 | 1.051 |
| ik | 0.998 | 0.964 | 1.021 | 1.037 | 1.011 | 1.047 | 1.002 | 0.948 | 1.054 |
| INDPRO | 1.107 | 1.036 | 1.000 | 1.022 | 1.088 | 0.984 | 1.057 | 0.994 | 1.150 |
| M1 | 1.131 | 1.110 | 1.106 | 1.107 | 1.159 | 1.088 | 1.092 | 1.226 | 0.964 |
| UNrate | 1.102 | 1.025 | 1.114 | 1.043 | 1.132 | 1.071 | 1.088 | 0.923$^{*}$ | 1.047 |
| GDP | 1.050 | 0.938$^{*}$ | 1.076 | 1.028 | 1.102 | 1.027 | 1.056 | 0.912$^{*}$ | 1.068 |
| USDAUS | 1.559 | 1.456 | 1.991 | 1.823 | 1.608 | 1.102 | 1.776 | 1.145 | 1.085 |
| USDINR | 1.019 | 1.011 | 0.984 | 0.960 | 0.999 | 1.005 | 0.989 | 0.995 | 1.114 |
| AR(1) | 1.000 | 1.121 | 1.240 | 1.170 | 1.048 | 1.882 | 1.608 | 1.140 | 1.165 |

This table reports the ratio of the mean squared forecast error of the univariate return prediction models that include a constant and the predictor variable listed in each row, to the mean squared forecast error of the benchmark model which assumes no predictability, $MSFE_{Univar}/MSFE_{Bench}$. The forecast evaluation period is 1971–2010. All of the forecasts are updated recursively, using a 20-year rolling estimation window. Commodity returns are based on the Reuters/Jeffries CRB spot price indexes. Values smaller than one indicate that the univariate models perform better than the benchmark. The statistical significance of the null of equal predictive ability is measured using the Clark and West (2007) test.

$^{***}$ Indicates significance at the 1% level.

$^{**}$ Indicates significance at the 5% level.

$^{*}$ Indicates significance at the 10% level.

## 4. Multivariate regressions

So far we have analyzed the effects of individual predictor variables on forecast performance. It is natural, however, to inquire what happens if multivariate information is used. To this end, we consider shrinkage methods such as ridge regressions and subset combinations, which are designed to reduce the effects of parameter estimation error on the forecasts. De Mol, Giannone, and Reichlin (2008) show, for a panel of predictor variables, that ridge regressions can be used to approximate the underlying factor structure. Groen and Pesenti (2011) use partial least squares and factor-augmented regressions to include multivariate information in their commodity price prediction models.

Ridge regression obtains parameters from a linear regression model subject to a penalty term

$$\hat{\beta}_\lambda = \arg\min_\beta \left( \sum_{t=1}^{T} (r_{t+1} - x_t'\beta)^2 + \lambda \sum_{j=1}^{K} \beta_j^2 \right). \quad (5)$$

**Table 3c**
Out-of-sample forecast performance: univariate prediction models, 1991–2010.

| | Panel A: Monthly | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Fats/oils | Foods | Industrials | Livestock | Metals | Textiles | Commodity | Stock | Bond |
| dp | 1.010 | 1.008 | 1.033 | 1.007 | 1.027 | 1.018 | 1.022 | 1.007 | 1.017 |
| tbl | 1.008 | 1.010 | 1.017 | 1.011 | 1.002 | 1.013 | 1.018 | 1.001 | 1.011 |
| ltr | 1.005 | 1.005 | 1.007 | 1.010 | 1.007 | 1.006 | 1.018 | 1.003 | 1.004 |
| tms | 1.005 | 1.008 | 0.999 | 1.004 | 1.004 | 1.000 | 1.006 | 1.005 | 1.007 |
| dfr | 1.013 | 1.025 | 0.974$^{*}$ | 0.983$^{*}$ | 0.971$^{*}$ | 1.020 | 1.007 | 1.043 | 1.017 |
| CPI | 0.995 | 0.995 | 1.015 | 0.993 | 1.031 | 0.991 | 1.004 | 1.014 | 0.995 |
| INDPRO | 1.017 | 1.011 | 1.013 | 1.021 | 1.014 | 1.008 | 1.014 | 1.008 | 1.011 |
| M1 | 1.011 | 1.013 | 1.009 | 1.020 | 1.008 | 0.989 | 1.015 | 0.994 | 1.021 |
| UNrate | 1.009 | 1.005 | 0.982$^{*}$ | 1.006 | 0.995 | 1.006 | 0.992$^{*}$ | 1.002 | 1.004 |
| USDAUS | 0.986$^{*}$ | 0.993 | 0.943$^{***}$ | 0.970$^{**}$ | 0.967$^{***}$ | 1.017 | 0.955$^{***}$ | 1.006 | 0.963$^{***}$ |
| USDINR | 0.992 | 0.993 | 0.945$^{***}$ | 0.988 | 0.966$^{**}$ | 0.981 | 0.948$^{**}$ | 1.001 | 0.980$^{**}$ |
| AR(1) | 0.999 | 1.010 | 0.907$^{***}$ | 0.996 | 0.933$^{***}$ | 1.012 | 0.954$^{**}$ | 1.005 | 1.002 |
| | *Panel B: Quarterly* | | | | | | | | |
| | Fats/oils | Foods | Industrials | Livestock | Metals | Textiles | Commodity | Stock | Bond |
| dp | 1.037 | 1.024 | 1.069 | 1.027 | 1.059 | 1.064 | 1.057 | 1.011 | 1.060 |
| tbl | 1.032 | 1.025 | 1.030 | 1.031 | 0.998 | 1.035 | 1.039 | 1.007 | 1.026 |
| ltr | 1.027 | 1.010 | 1.034 | 1.025 | 1.028 | 1.053 | 1.033 | 1.008 | 1.032 |
| tms | 1.013 | 1.024 | 0.995 | 1.006 | 1.010 | 0.974$^{*}$ | 1.009 | 1.020 | 1.017 |
| dfr | 1.078 | 1.060 | 0.988 | 1.070 | 0.984 | 1.027 | 1.027 | 1.074 | 1.047 |
| CPI | 0.908$^{**}$ | 0.996$^{*}$ | 0.878 | 0.893$^{*}$ | 0.922 | 1.003 | 0.902$^{*}$ | 0.999 | 0.979 |
| ik | 0.997 | 0.993 | 0.901$^{***}$ | 1.011 | 0.920$^{***}$ | 0.953$^{**}$ | 0.921$^{***}$ | 1.028 | 1.036 |
| INDPRO | 1.051 | 1.010 | 1.101 | 1.069 | 1.085 | 1.034 | 1.078 | 1.071 | 1.055 |
| M1 | 1.024 | 1.009 | 0.942$^{*}$ | 1.019 | 0.955$^{*}$ | 1.035 | 0.993 | 1.037 | 1.031 |
| UNrate | 1.012 | 1.007 | 0.962$^{*}$ | 1.002 | 0.991 | 0.950$^{*}$ | 0.974$^{*}$ | 1.002 | 1.013 |
| USDAUS | 1.026 | 1.004 | 0.944$^{**}$ | 1.019 | 0.983 | 0.997 | 0.975$^{*}$ | 1.054 | 1.059 |
| USDINR | 0.961$^{**}$ | 0.967$^{**}$ | 0.950$^{**}$ | 0.945$^{**}$ | 0.985 | 0.978$^{*}$ | 0.935$^{**}$ | 1.011 | 0.903$^{***}$ |
| AR(1) | 1.013 | 1.036 | 0.946$^{**}$ | 1.017 | 0.986 | 0.962$^{**}$ | 0.994 | 1.014 | 1.019 |
| | *Panel C: Annual* | | | | | | | | |
| | Fats/oils | Foods | Industrials | Livestock | Metals | Textiles | Commodity | Stock | Bond |
| dp | 1.165 | 1.200 | 1.148 | 1.131 | 1.133 | 1.216 | 1.159 | 1.029 | 1.181 |
| tbl | 1.025 | 1.050 | 0.896$^{*}$ | 0.944 | 0.830$^{*}$ | 1.047 | 0.912$^{*}$ | 1.077 | 1.083 |
| ltr | 1.098 | 0.970 | 1.077 | 1.101 | 1.044 | 1.155 | 1.102 | 1.053 | 0.918$^{**}$ |
| tms | 1.010 | 1.085 | 0.889$^{**}$ | 0.922$^{*}$ | 0.946 | 0.883$^{**}$ | 0.913$^{*}$ | 1.042 | 1.049 |
| dfr | 1.219 | 1.200 | 1.468 | 1.319 | 1.428 | 1.272 | 1.446 | 1.294 | 1.094 |
| CPI | 0.940 | 0.961 | 0.846 | 0.848$^{*}$ | 0.817 | 0.980 | 0.862 | 1.052 | 0.955 |
| ik | 0.865$^{**}$ | 0.972 | 0.831$^{***}$ | 0.986 | 0.870$^{***}$ | 0.987 | 0.805$^{***}$ | 1.061 | 1.201 |
| INDPRO | 0.703$^{*}$ | 0.676$^{*}$ | 0.881$^{**}$ | 0.750$^{*}$ | 0.969$^{**}$ | 0.916$^{*}$ | 0.749$^{**}$ | 1.230 | 1.060 |
| M1 | 1.126 | 1.088 | 1.092 | 1.268 | 1.057 | 1.206 | 1.093 | 1.164 | 1.153 |
| UNrate | 1.034 | 1.015 | 1.053 | 1.038 | 1.048 | 1.116 | 1.038 | 0.913 | 1.017 |
| GDP | 0.748$^{*}$ | 0.789$^{*}$ | 0.926$^{*}$ | 0.803$^{*}$ | 1.006$^{*}$ | 0.995 | 0.824$^{*}$ | 1.080 | 1.101 |
| USDINR | 1.076 | 1.067 | 1.066 | 1.110 | 1.090 | 1.002 | 1.097 | 1.051 | 1.550 |
| AR(1) | 1.117 | 1.079 | 1.155 | 1.126 | 1.180 | 1.092 | 1.167 | 1.204 | 0.915$^{**}$ |

This table reports the ratio of the mean squared forecast error of the univariate return prediction models that include a constant and the predictor variable listed in each row, to the mean squared forecast error of the benchmark model which assumes no predictability, $\mathrm{MSFE}_{\mathrm{Univar}}/\mathrm{MSFE}_{\mathrm{Bench}}$. The forecast evaluation period is 1991–2010. All of the forecasts are updated recursively, using a 20-year rolling estimation window. Commodity returns are based on the Reuters/Jeffries CRB spot price indexes. Values smaller than one indicate that the univariate models perform better than the benchmark. The statistical significance of the null of equal predictive ability is measured using the Clark and West (2007) test.
$^{***}$ Indicates statistical significance at the 1% level.
$^{**}$ Indicates statistical significance at the 5% level.
$^{*}$ Indicates statistical significance at the 10% level.

Following Inoue and Killian (2008), we consider a range of values $\lambda \in \{0.5, 5, 10, 20, 50, 100, 150, 200, 1000\}$. As $\lambda \to \infty$, $\hat{r}_{t+1|t} \to \frac{1}{T}\sum_{j=1}^{T} r_j$, so the ridge forecast simply converges to the sample mean.

For a given value of $\lambda$, the ridge forecasts are computed as[9]

$$\hat{r}_{t+1|t} = x_t' \hat{\beta}_\lambda. \quad (6)$$

The subset regression approach, recently introduced by Elliott, Gargano, and Timmermann (2013), uses equally-weighted combinations of forecasts based on all possible models that include a particular subset of the predictor variables. Suppose that 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 include a specified number of regressors, $k \le K$. Specifically, we first estimate regressions using a particular subset of the predictor variables. Next, we average the results across all $k \le K$

9 Prior to estimating the ridge coefficients, the predictors and the dependent variable are standardized. The out-of-sample forecasts are obtained using the original predictors and the rescaled ridge coefficients.

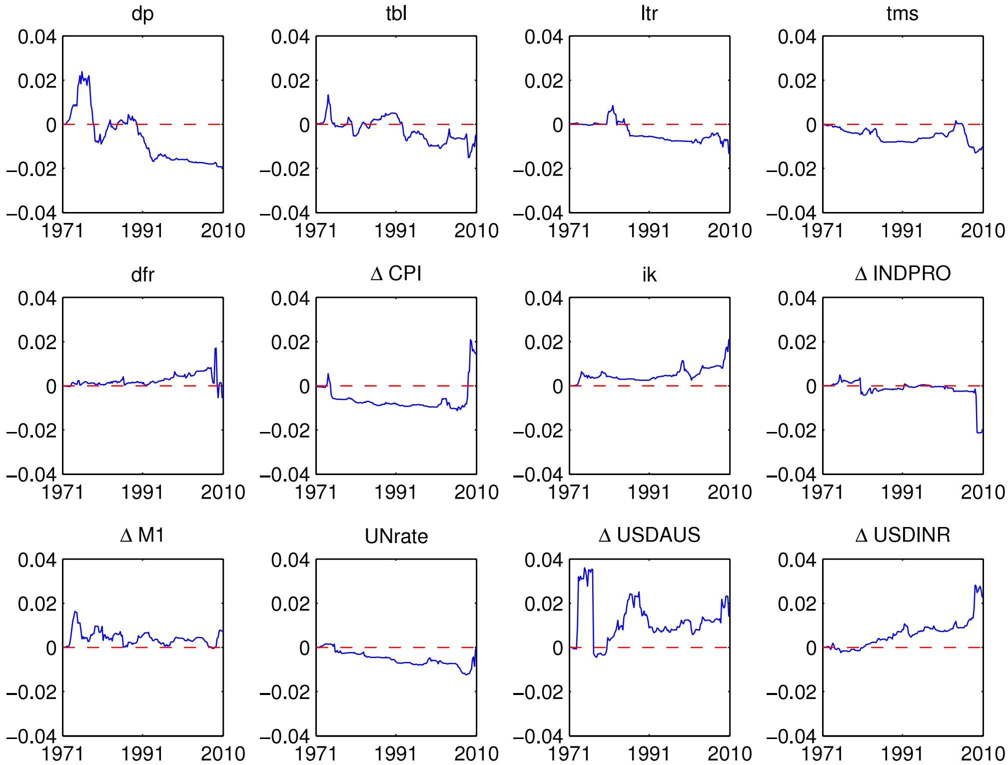


**Fig. 3.** *CUMSUM analysis, commodity index.* This figure plots the cumulated difference between the quarterly squared forecast errors of the benchmark model and the univariate models containing the variables listed on top of each graph: the dividend-price ratio (dp), the 3-month T-bill rate (tbl), the long term return (ltr), the term spread (tms), the default return spread (dfr), inflation ( CPI), the investment–capital ratio (ik), growth in industrial production ( IND), money supply growth ( M1), the unemployment rate (UNrate), and the change in the exchange rate of the US dollar to the Australian dollar ( USDAUD) and the Indian rupee ( USDINR). The dependent variable is the return on the Reuters/Jeffries-CRB spot price commodity index, compiled by the Commodity Research Bureau.

dimensional subsets of the regressors in order to provide an estimator, $\hat{\beta}$, that is used to generate the forecasts. With $K$ regressors in the full model and $k$ regressors chosen for each of the short models, there are $c_k^K = K!/(k!(K \quad k)!)$ subset regressions to average over. As a special case, the univariate case ($k = 1$) has $K$ such regressions, each using a single variable. The equal-weighted combination of the forecasts from the individual models is then

$$\hat{r}_{t+1|t} = \frac{1}{K}\sum_{i=1}^{K} x'_{ti}\hat{\beta}_{it}. \tag{7}$$

This strategy was used by Rapach et al. (2010) to study the predictability of US stock returns. More generally, the forecasts from the subset regressions are given as

$$\hat{r}_{t+1|t} = \frac{1}{C_k^K}\sum_{i=1}^{C_k^K} x'_{ti}\hat{\beta}_{it}, \tag{8}$$

where $\dim(x_{ti}) = k$, so that $x_{ti}$ has $k$ elements.

### 4.1. Empirical results

Table 4 reports results from the multivariate analysis. At the monthly horizon, the ridge and subset regressions show essentially no improvements for fats/oils, foods, and livestock, and only marginal improvements for textiles. In contrast, we find significant improvements of 5%–10% for the best ridge and subset regression schemes for industrials, metals, and the broad commodity price index.

The improvements in predictive accuracy from multivariate regressions fitted to the quarterly series are even greater, getting as large as 14% for industrials and the general commodity price index. Moreover, improvements in quarterly price forecasts are now seen for foods, industrials, livestock, metals, and textiles, with only fats/oils missing out. At the annual horizon, the evidence of predictability from the multivariate approaches is weaker in both frequency and magnitude than at the monthly and quarterly horizons. Moreover, at this longer horizon, there are many cases in which the models that include many predictors or apply less shrinkage, produce very poor out-of-sample predictions. This is to be expected, given the short sample (20 observations) used to estimate the parameters of the multivariate model.

The simple equal-weighted average of all possible univariate forecasts is shown as the first line ($k = 1$) under the subset regressions. Rapach et al. (2010) found that this method provided good out-of-sample forecasts for stock returns. At the monthly horizon, the MSE reduction for industrials and the broad commodity index is around 3% under this approach. This rises to around 6% at the quarterly horizon, before dropping to 4% at the annual horizon. In fact, this strategy is dominated by the combination of forecasts from models with more predictor variables. In many

**Table 4**
Out-of-sample forecast performance: multivariate models, 1971–2010.

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | *Panel A: Monthly* | | | | | | | | |
| | *A.1 Ridge regression* | | | | | | | | |
| $\lambda$ | Fats/oils | Foods | Industrials | Livestock | Metals | Textiles | Commodity | Stock | Bond |
| 0.5 | 1.100 | 1.121 | 0.976$^{***}$ | 1.102 | 1.015 | 1.072 | 1.027 | 1.093 | 1.002 |
| 5 | 1.091 | 1.111 | 0.965$^{***}$ | 1.092 | 1.005 | 1.059 | 1.016 | 1.077 | 0.990$^{***}$ |
| 10 | 1.083 | 1.103 | 0.956$^{***}$ | 1.084 | 0.997$^{***}$ | 1.049 | 1.008 | 1.066 | 0.983$^{***}$ |
| 20 | 1.071 | 1.090 | 0.944$^{***}$ | 1.073 | 0.986$^{***}$ | 1.036 | 0.996$^{***}$ | 1.053 | 0.973$^{***}$ |
| 50 | 1.051 | 1.068 | 0.925$^{***}$ | 1.052 | 0.967$^{***}$ | 1.015 | 0.977$^{***}$ | 1.030 | 0.961$^{***}$ |
| 100 | 1.033 | 1.047 | 0.912$^{***}$ | 1.033 | 0.953$^{***}$ | 0.999$^{**}$ | 0.962$^{***}$ | 1.013 | 0.955$^{***}$ |
| 150 | 1.024 | 1.035 | 0.908$^{***}$ | 1.022 | 0.946$^{***}$ | 0.992$^{**}$ | 0.955$^{***}$ | 1.004 | 0.953$^{***}$ |
| 200 | 1.017 | 1.027 | 0.906$^{***}$ | 1.014 | 0.943$^{***}$ | 0.988$^{**}$ | 0.951$^{***}$ | 0.998$^{**}$ | 0.953$^{***}$ |
| 1000 | 0.999 | 1.001 | 0.937$^{***}$ | 0.994$^{*}$ | 0.958$^{***}$ | 0.985$^{**}$ | 0.962$^{***}$ | 0.988$^{**}$ | 0.972$^{***}$ |
| 5000 | 0.999 | 0.999 | 0.980$^{***}$ | 0.997$^{*}$ | 0.986$^{***}$ | 0.995$^{*}$ | 0.987$^{***}$ | 0.995$^{**}$ | 0.991$^{***}$ |
| | *A.2 Subset regression* | | | | | | | | |
| $k$ | Fats/oils | Foods | Industrials | Livestock | Metals | Textiles | Commodity | Stock | Bond |
| 1 | 0.999 | 0.999 | 0.964$^{***}$ | 0.995$^{*}$ | 0.975$^{***}$ | 0.991$^{*}$ | 0.978$^{***}$ | 0.992$^{**}$ | 0.985$^{***}$ |
| 2 | 1.000 | 1.001 | 0.939$^{***}$ | 0.994$^{*}$ | 0.959$^{***}$ | 0.987$^{*}$ | 0.963$^{***}$ | 0.988$^{**}$ | 0.974$^{***}$ |
| 3 | 1.003 | 1.006 | 0.923$^{***}$ | 0.997$^{*}$ | 0.950$^{***}$ | 0.985$^{*}$ | 0.955$^{***}$ | 0.987$^{**}$ | 0.966$^{***}$ |
| 4 | 1.007 | 1.012 | 0.914$^{***}$ | 1.001 | 0.945$^{***}$ | 0.985$^{*}$ | 0.952$^{***}$ | 0.989$^{**}$ | 0.961$^{***}$ |
| 5 | 1.013 | 1.021 | 0.910$^{***}$ | 1.008 | 0.945$^{***}$ | 0.988$^{*}$ | 0.953$^{***}$ | 0.993$^{**}$ | 0.959$^{***}$ |
| 6 | 1.021 | 1.031 | 0.911$^{***}$ | 1.017 | 0.948$^{***}$ | 0.993$^{*}$ | 0.956$^{***}$ | 0.999$^{**}$ | 0.958$^{***}$ |
| 7 | 1.030 | 1.042 | 0.915$^{***}$ | 1.027 | 0.954$^{***}$ | 1.000 | 0.963$^{***}$ | 1.007 | 0.959$^{***}$ |
| 8 | 1.041 | 1.055 | 0.922$^{***}$ | 1.039 | 0.962$^{***}$ | 1.010 | 0.971$^{***}$ | 1.018 | 0.963$^{***}$ |
| 9 | 1.053 | 1.069 | 0.931$^{***}$ | 1.052 | 0.972$^{***}$ | 1.022 | 0.982$^{***}$ | 1.032 | 0.969$^{***}$ |
| 10 | 1.068 | 1.085 | 0.944$^{***}$ | 1.067 | 0.985$^{***}$ | 1.036 | 0.995$^{***}$ | 1.049 | 0.977$^{***}$ |
| | *Panel B: Quarterly* | | | | | | | | |
| | *B.1 Ridge regression* | | | | | | | | |
| $\lambda$ | Fats/oils | Foods | Industrials | Livestock | Metals | Textiles | Commodity | Stock | Bond |
| 0.5 | 1.305 | 1.330 | 1.095 | 1.224 | 1.283 | 1.205 | 1.049 | 1.439 | 1.283 |
| 5 | 1.208 | 1.213 | 1.001 | 1.137 | 1.173 | 1.112 | 0.970$^{***}$ | 1.263 | 1.122 |
| 10 | 1.158 | 1.153 | 0.956$^{***}$ | 1.086 | 1.119 | 1.069 | 0.934$^{***}$ | 1.193 | 1.072 |
| 20 | 1.105 | 1.089 | 0.911$^{***}$ | 1.027 | 1.062 | 1.022 | 0.896$^{***}$ | 1.125 | 1.030 |
| 50 | 1.040 | 1.014 | 0.864$^{***}$ | 0.959$^{***}$ | 0.997$^{**}$ | 0.968$^{***}$ | 0.858$^{***}$ | 1.050 | 0.989$^{**}$ |
| 100 | 1.008 | 0.979$^{**}$ | 0.853$^{***}$ | 0.933$^{***}$ | 0.966$^{**}$ | 0.945$^{***}$ | 0.852$^{***}$ | 1.013 | 0.973$^{**}$ |
| 150 | 0.997 | 0.970$^{**}$ | 0.859$^{***}$ | 0.931$^{***}$ | 0.957$^{**}$ | 0.941$^{***}$ | 0.860$^{***}$ | 1.000 | 0.969$^{**}$ |
| 200 | 0.992 | 0.967$^{**}$ | 0.867$^{***}$ | 0.934$^{***}$ | 0.955$^{**}$ | 0.942$^{***}$ | 0.870$^{***}$ | 0.993 | 0.970$^{**}$ |
| 1000 | 0.991 | 0.981$^{**}$ | 0.943$^{***}$ | 0.972$^{***}$ | 0.975$^{**}$ | 0.974$^{***}$ | 0.946$^{***}$ | 0.990 | 0.986$^{**}$ |
| 5000 | 0.997 | 0.995$^{**}$ | 0.985$^{***}$ | 0.993$^{***}$ | 0.993$^{**}$ | 0.993$^{***}$ | 0.986$^{***}$ | 0.997 | 0.996$^{**}$ |
| | *B.2 Subset regression* | | | | | | | | |
| $k$ | Fats/oils | Foods | Industrials | Livestock | Metals | Textiles | Commodity | Stock | Bond |
| 1 | 0.991 | 0.979$^{**}$ | 0.936$^{***}$ | 0.970$^{***}$ | 0.971$^{**}$ | 0.971$^{***}$ | 0.940$^{***}$ | 0.988 | 0.986$^{**}$ |
| 2 | 0.991 | 0.971$^{**}$ | 0.896$^{***}$ | 0.952$^{***}$ | 0.959$^{**}$ | 0.953$^{***}$ | 0.901$^{***}$ | 0.986 | 0.978$^{**}$ |
| 3 | 0.996 | 0.971$^{*}$ | 0.873$^{***}$ | 0.942$^{***}$ | 0.957$^{**}$ | 0.944$^{***}$ | 0.878$^{***}$ | 0.991 | 0.975$^{**}$ |
| 4 | 1.006 | 0.977$^{*}$ | 0.862$^{***}$ | 0.941$^{***}$ | 0.962$^{**}$ | 0.942$^{***}$ | 0.865$^{***}$ | 1.002 | 0.978$^{**}$ |
| 5 | 1.019 | 0.990$^{*}$ | 0.860$^{***}$ | 0.948$^{***}$ | 0.974$^{**}$ | 0.948$^{***}$ | 0.860$^{***}$ | 1.017 | 0.987$^{**}$ |
| 6 | 1.037 | 1.010 | 0.866$^{***}$ | 0.961$^{***}$ | 0.991$^{**}$ | 0.959$^{***}$ | 0.863$^{***}$ | 1.036 | 1.000 |
| 7 | 1.058 | 1.035 | 0.880$^{***}$ | 0.982$^{***}$ | 1.014 | 0.977$^{***}$ | 0.872$^{***}$ | 1.062 | 1.020 |
| 8 | 1.085 | 1.067 | 0.901$^{***}$ | 1.009 | 1.043 | 1.001 | 0.888$^{***}$ | 1.094 | 1.045 |
| 9 | 1.117 | 1.106 | 0.929$^{***}$ | 1.044 | 1.080 | 1.030 | 0.911$^{***}$ | 1.136 | 1.078 |
| 10 | 1.157 | 1.154 | 0.965$^{***}$ | 1.085 | 1.125 | 1.067 | 0.940$^{***}$ | 1.191 | 1.120 |
| | *Panel C: Annual* | | | | | | | | |
| | *C.1 Ridge regression* | | | | | | | | |
| $\lambda$ | Fats/oils | Foods | Industrials | Livestock | Metals | Textiles | Commodity | Stock | Bond |
| 0.5 | 2.572 | 2.439 | 2.641 | 2.334 | 2.054 | 4.277 | 2.912 | 2.337 | 2.058 |
| 5 | 1.433 | 1.324 | 1.273 | 1.279 | 1.200 | 1.976 | 1.411 | 1.393 | 1.395 |
| 10 | 1.237 | 1.134 | 1.096 | 1.126 | 1.066 | 1.630 | 1.188 | 1.238 | 1.255 |
| 20 | 1.105 | 1.010 | 0.996$^{*}$ | 1.026 | 0.990$^{*}$ | 1.381 | 1.047 | 1.117 | 1.129 |
| 50 | 1.011 | 0.939$^{*}$ | 0.948$^{**}$ | 0.960$^{*}$ | 0.956$^{**}$ | 1.173 | 0.963$^{**}$ | 1.018 | 1.020 |
| 100 | 0.986 | 0.935$^{*}$ | 0.950$^{**}$ | 0.950$^{*}$ | 0.959$^{**}$ | 1.087 | 0.952$^{**}$ | 0.988 | 0.987 |

(*continued on next page*)

Table 4 (*continued*)

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 150 | 0.982 | 0.944* | 0.957** | 0.955* | 0.966** | 1.056 | 0.956** | 0.983 | 0.982 |
| 200 | 0.982 | 0.951* | 0.963** | 0.960* | 0.970** | 1.041 | 0.961** | 0.982 | 0.982 |
| 1000 | 0.993 | 0.985* | 0.989** | 0.987* | 0.991** | 1.007 | 0.988** | 0.993 | 0.993 |
| 5000 | 0.998 | 0.996* | 0.997** | 0.997* | 0.998** | 1.001 | 0.997** | 0.998 | 0.998 |

| | *C.2 Subset regression* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| *k* | Fats/oils | Foods | Industrials | Livestock | Metals | Textiles | Commodity | Stock | Bond |
| 1 | 0.979 | 0.950* | 0.962** | 0.957* | 0.969** | 1.040 | 0.960** | 0.980 | 0.979 |
| 2 | 0.988 | 0.931* | 0.943** | 0.945* | 0.952** | 1.102 | 0.945** | 0.990 | 0.987 |
| 3 | 1.024 | 0.946* | 0.944** | 0.959* | 0.951** | 1.191 | 0.957** | 1.028 | 1.023 |
| 4 | 1.086 | 0.992* | 0.970** | 0.996* | 0.967** | 1.310 | 0.998** | 1.088 | 1.083 |
| 5 | 1.172 | 1.072 | 1.026 | 1.054 | 1.006 | 1.465 | 1.070 | 1.168 | 1.164 |
| 6 | 1.284 | 1.184 | 1.118 | 1.137 | 1.069 | 1.668 | 1.178 | 1.271 | 1.267 |
| 7 | 1.423 | 1.327 | 1.258 | 1.251 | 1.164 | 1.942 | 1.332 | 1.399 | 1.394 |
| 8 | 1.595 | 1.506 | 1.465 | 1.411 | 1.296 | 2.324 | 1.549 | 1.562 | 1.552 |
| 9 | 1.816 | 1.732 | 1.765 | 1.637 | 1.482 | 2.864 | 1.854 | 1.780 | 1.761 |
| 10 | 2.125 | 2.039 | 2.204 | 1.967 | 1.756 | 3.638 | 2.291 | 2.095 | 2.056 |

This table reports the mean squared forecast errors ratios, $MSFE_{Multi}/MSE_{Bench}$, for a range of multivariate estimation methods. Ridge regression includes all of the predictor variables in the forecasting model, but shrinks, through $\lambda$, 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. All estimation is conducted recursively, using a 20-year rolling estimation window and 1971–2010 as the out-of-sample forecast evaluation period. Commodity returns are based on the Reuters/Jeffries CRB spot price indexes. The statistical significance is measured using the Clark and West (2007) test for out-of-sample predictive accuracy, using the prevailing mean model, which only includes a constant, as the benchmark.

*** Indicates statistical significance at the 1% level.

** Indicates statistical significance at the 5% level.

* Indicates statistical significance at the 10% level.

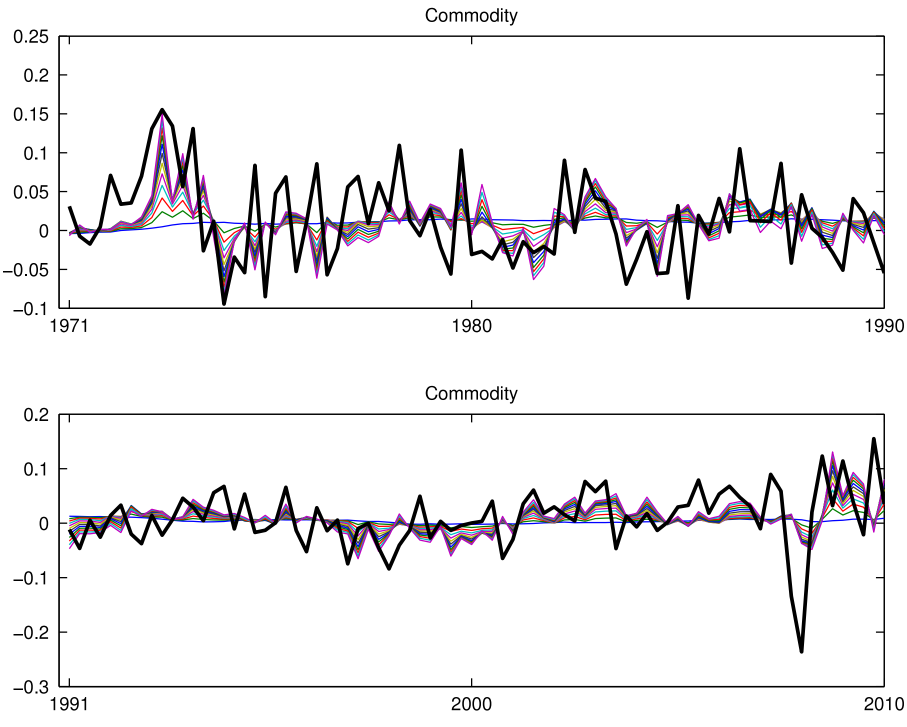


**Fig. 4.** *Forecasts from complete subset regressions.* The figure plots the quarterly forecasts for the complete subset regressions that combine forecasts from all possible models with $k = 1, 2, \ldots, 13$ predictor variables. The thick black line tracks the actual (realized) return on the Reuters/Jeffries-CRB spot price commodity index.

cases, including 2–4 predictor variables lowers the MSE by a substantial amount compared with the equal-weighted combination of univariate forecasts. This suggests that the best models include relatively large numbers of predictors.

Fig. 4 plots the quarterly out-of-sample forecasts of the broad commodity price changes generated by the complete subset regressions. Each line corresponds to a different value, *k*, tracking the number of variables included in the prediction model. The smaller the number of variables included in the models, the smoother the averaged forecast tends to be. The figure illustrates that, although the forecasting models clearly missed the

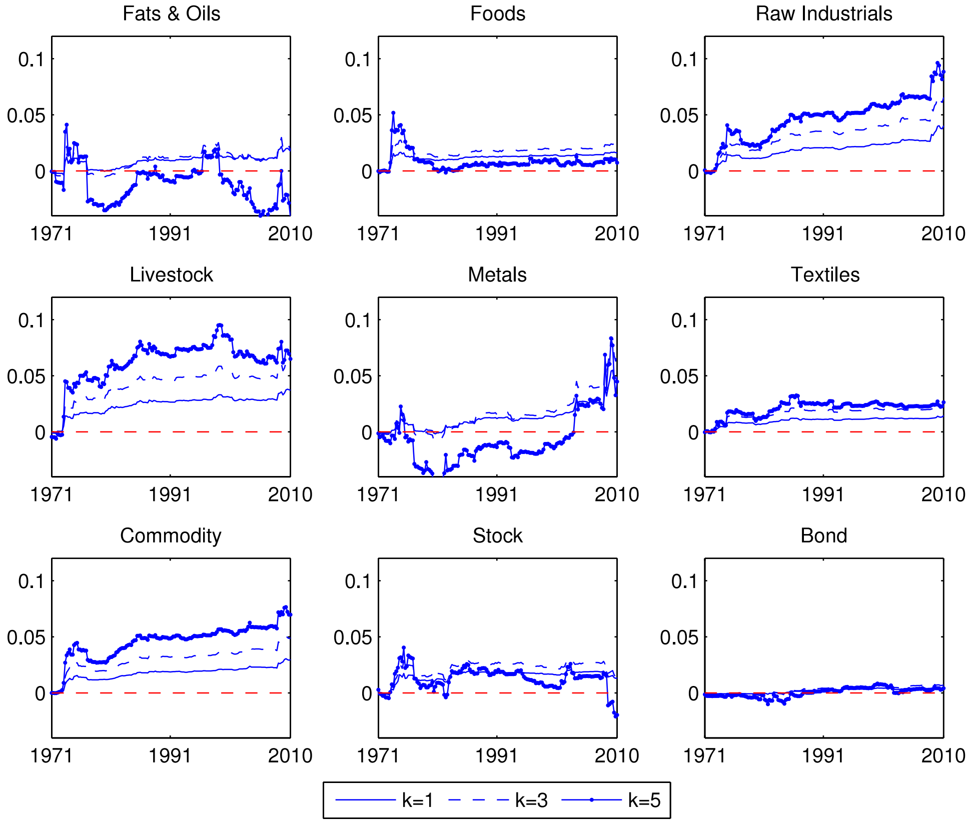


**Fig. 5.** *CUMSUM analysis, subset regression.* This figure shows the cumulated difference between the squared forecast errors of the benchmark model and the complete subset regressions which combine forecasts from all possible models with $k = 1$, $k = 3$, and $k = 5$ predictors, for the indexes listed at the top of each graph.

magnitude of the decline in commodity prices in 2008, they did a better job at predicting the subsequent bounceback in 2009 and 2010.

Fig. 5 plots the cumulated sum of squared forecast error differentials for subset regressions with $k = 1, 3$, and 5 predictors. These figures allow us to identify periods in which the multivariate prediction models beat the benchmarks. For raw industrials, livestock, textiles, and the broad commodity price index, the outperformance is consistent throughout most of the sample, although with particularly good performances in the early 1970s and during the financial crisis of 2008–2009. Conversely, fats and oils, foods, and metals see a spell of very poor forecast performance in the mid-seventies, as do the models for stock and bond returns. These graphs suggest that the multivariate models manage to deliver consistently better forecasts than the benchmarks for at least some of the commodity indexes.

Comparing the plots for the three values of $k$ (the number of predictors in each model entering the forecast combinations), it is clear that the best strategy for livestock, raw industrials, textiles, and general commodity prices requires the combination of multivariate models. Conversely, for fats and oils, foods, and metals, it is not clear that one can do better than simply taking an equal-weighted average of the univariate forecasts.

## 5. Forecasting performance in recessions and expan sions

Studies such as those by Henkel et al. (2011) and Rapach et al. (2010) find that the 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 whether there is state-dependence in the strength of the predictive evidence. Since it is an ex-post measure of the state of the economy, the popular NBER recession index is not suitable for a proper out-of-sample analysis.[10] Instead, to identify recessions, we define an indicator variable based on the unemployment recession gap proposed by Stock and Watson (2010):

$$\tilde{U}_t = \begin{cases} 1 & \text{if } U_t^* = U_t \quad \dfrac{1}{36}\sum_{\tau=1}^{36} U_t \quad _\tau > 0.5 \\ 0 & \text{otherwise.} \end{cases} \tag{9}$$

Here, $U_t$ is the (vintage) monthly unemployment ratio. Stock and Watson (2010) find that this measure lines up well with the NBER recessions determined ex-post.

10 We thank an anonymous referee for this suggestion.

**Table 5**
Out-of-sample forecast performances in recessions versus expansions.

| | Fats/oils | Foods | Industrials | Livestock | Metals | Textiles | Commodity | Stock | Bond |
|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Univariate* | | | | | | | | | |
| dp | 0.988 | 0.978** | 0.977 | 1.002 | 0.978 | 0.996 | 0.960 | 0.943*** | 0.978 |
| tbl | 1.011 | 1.037 | 0.999 | 0.997 | 1.004 | 1.009 | 1.028 | 1.062 | 1.013 |
| ltr | 0.995 | 1.011 | 1.009 | 1.013 | 1.017 | 0.998 | 1.012 | 1.004 | 1.032 |
| tms | 0.992 | 0.998 | 0.939** | 0.997 | 0.975* | 0.962* | 0.965* | 0.994 | 1.002 |
| dfr | 1.013 | 1.016 | 0.970 | 0.966 | 0.970 | 1.009 | 0.994 | 1.024 | 1.023 |
| CPI | 1.013 | 1.008 | 1.007 | 1.004 | 1.035 | 0.993** | 1.002 | 1.067 | 0.998 |
| INDPRO | 1.012 | 1.022 | 1.008 | 1.040 | 1.018 | 1.017 | 1.012 | 1.004 | 1.003 |
| M1 | 0.999 | 1.029 | 0.974 | 1.016 | 0.994 | 0.958 | 1.003 | 0.986** | 1.025 |
| UNRATE | 1.003 | 1.004 | 0.958*** | 1.000 | 0.978* | 1.000 | 0.976*** | 0.982* | 0.998 |
| USDAUS | 0.974** | 0.975 | 0.971*** | 0.885** | 0.966*** | 1.039 | 0.936*** | 0.970 | 0.982 |
| USDINR | 0.980* | 1.001 | 0.956** | 0.980** | 0.968* | 0.935* | 0.955 | 0.998 | 1.010 |
| AR(1) | 0.989 | 0.983 | 0.898** | 1.027 | 0.941* | 0.992 | 0.938 | 1.027 | 1.023 |
| *Panel B: Ridge* | | | | | | | | | |
| | Fats/oils | Foods | Industrials | Livestock | Metals | Textiles | Commodity | Stock | Bond |
| 0.5 | 1.020 | 1.008 | 0.955 | 0.965 | 1.014 | 1.014 | 0.945 | 1.034 | 1.062 |
| 10 | 1.016 | 1.014 | 0.946 | 0.961 | 1.006 | 0.997 | 0.944 | 1.038 | 1.072 |
| 20 | 1.011 | 1.016 | 0.939* | 0.960 | 0.999 | 0.987 | 0.943* | 1.034 | 1.074 |
| 50 | 1.002 | 1.020 | 0.924** | 0.961 | 0.985 | 0.973* | 0.941* | 1.023 | 1.072 |
| 100 | 0.995 | 1.020 | 0.914** | 0.966 | 0.972 | 0.967* | 0.941** | 1.013 | 1.066 |
| 150 | 0.991 | 1.019 | 0.910** | 0.969 | 0.965* | 0.966** | 0.942** | 1.007 | 1.060 |
| 200 | 0.989 | 1.017 | 0.910** | 0.972 | 0.961* | 0.966** | 0.943** | 1.004 | 1.055 |
| 1000 | 0.990 | 1.005 | 0.942*** | 0.985 | 0.967** | 0.982** | 0.964** | 0.999 | 1.023 |
| 5000 | 0.996 | 1.000 | 0.982*** | 0.995 | 0.989** | 0.995** | 0.988** | 0.999 | 1.006 |
| *Panel C: Subset* | | | | | | | | | |
| | Fats/oils | Foods | Industrials | Livestock | Metals | Textiles | Commodity | Stock | Bond |
| 1 | 0.994 | 1.002 | 0.966*** | 0.991 | 0.979** | 0.990** | 0.979** | 1.000 | 1.011 |
| 2 | 0.990 | 1.005 | 0.941*** | 0.986 | 0.966** | 0.983** | 0.964** | 1.000 | 1.021 |
| 3 | 0.989 | 1.009 | 0.924*** | 0.982 | 0.958** | 0.977** | 0.955** | 1.000 | 1.031 |
| 4 | 0.989 | 1.013 | 0.914** | 0.979 | 0.955** | 0.974** | 0.949** | 1.002 | 1.039 |
| 5 | 0.990 | 1.017 | 0.909** | 0.976 | 0.956* | 0.973** | 0.946** | 1.005 | 1.046 |
| 6 | 0.993 | 1.020 | 0.909** | 0.974 | 0.959* | 0.974** | 0.945** | 1.010 | 1.053 |
| 7 | 0.997 | 1.022 | 0.913** | 0.972 | 0.965 | 0.977* | 0.945* | 1.016 | 1.058 |
| 8 | 1.001 | 1.023 | 0.919* | 0.970 | 0.973 | 0.982 | 0.946* | 1.022 | 1.062 |
| 9 | 1.006 | 1.022 | 0.928* | 0.968 | 0.982 | 0.989 | 0.947* | 1.028 | 1.064 |
| 10 | 1.011 | 1.019 | 0.937 | 0.966 | 0.993 | 0.997 | 0.947 | 1.034 | 1.065 |

This table compares ratios of the mean squared forecast errors of monthly return prediction models in recessions versus expansions, $MSFE_{Rec}/MSFE_{Exp}$. Recessions are defined by the recession indicator based on the 'unemployment recession gap' of Stock and Watson (2010). The forecast evaluation period is 1971–2010. All of the forecasts are updated recursively, using a 20-year rolling estimation window. Commodity 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 lower in recessions than in expansions.
*** Indicates statistical significance at the 1% level.
** Indicates statistical significance at the 5% level.
* Indicates statistical significance at the 10% level.

We evaluate the statistical significance of differences in predictive power in recessions relative to expansions using regressions of the squared error return difference on the recession indicator defined in Eq. (9):

$$(r_{t+1:t+h} - \bar{r}_{t+1:t+h|t})^2 - (r_{t+1:t+h} - \hat{r}_{t+1:t+h|t})^2$$
$$= \alpha + \beta \tilde{U}_{t+1} + \varepsilon_{t+1:t+h}. \tag{10}$$

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

Table 5 reports the MSEs in recessions relative to the MSEs during expansions, with values below one suggesting that the MSE values are lowest in recessions. The results suggest that the predictive accuracy of most models tends to be slightly better during recessions than expansions. Moreover, the improvement in predictive power measured through the slope coefficient $\beta$ in Eq. (10) is statistically significant for some of the predictors, such as the unemployment rate, the term spread, and the US–Australian dollar exchange rate. For the multivariate regressions, the results are even stronger, particularly for industrials, livestock, metals, textiles, and the broad commodity index.

We next explore why the predictability is stronger during recessions than expansions. A simple decomposition of the predictive $R^2$, $R^2 = \beta^2\sigma_x^2/(\beta^2\sigma_x^2 + \sigma_\varepsilon^2)$, shows that the precision of the forecasts is (i) decreasing with the noise of the predictive regression, $\sigma_\varepsilon^2$; (ii) increasing with the

**Table 6**
Decomposition of forecasting performances in recessions versus expansions.

| | $\beta = \hat{\beta}^2_{\text{Rec}}/\hat{\beta}^2_{\text{Exp}}$ | | | | | | | | | $\sigma_x^2 = \frac{\sigma^2_{x,Rec}}{\sigma^2_{x,Exp}}$ | $\sigma_\epsilon^2 = \hat{\sigma}^2_{\epsilon,Rec}/\hat{\sigma}^2_{\epsilon,\text{Exp}}$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Fats/oils | Foods | Industrials | Livestock | Metals | Textiles | Commodity | Stock | Bond | | Fats/oils | Foods | Industrials | Livestock | Metals | Textiles | Commodity | Stock | Bond |
| dp | 1.829 | 3.886 | 20.066 | 2.385 | 45.488 | 5.837 | 26.159 | 6.753 | 3.172 | 0.817 | 1.087 | 1.067 | 1.384 | 1.148 | 1.790 | 1.274 | 1.202 | 1.353 | 1.953 |
| tbl | 1.188 | 13.060 | 4.209 | 1.833 | 14.127 | 1.309 | 4.662 | 0.047 | 0.984 | 2.736 | 1.089 | 1.071 | 1.380 | 1.152 | 1.783 | 1.273 | 1.208 | 1.410 | 1.957 |
| ltr | 0.331 | 1.472 | 0.814 | 0.048 | 0.900 | 0.275 | 0.317 | 1.004 | 0.364 | 2.250 | 1.090 | 1.067 | 1.424 | 1.157 | 1.828 | 1.294 | 1.237 | 1.401 | 1.986 |
| tms | 7.532 | 2.619 | 18.071 | 27.384 | 21.970 | 3.692 | 7.377 | 0.246 | 0.513 | 1.697 | 1.077 | 1.058 | 1.319 | 1.131 | 1.746 | 1.263 | 1.158 | 1.411 | 1.985 |
| dfr | 1.443 | 1.533 | 2.641 | 12.727 | 1.704 | 5.330 | 10.404 | 1.398 | 0.158 | 3.017 | 1.074 | 1.060 | 1.339 | 1.091 | 1.744 | 1.258 | 1.163 | 1.405 | 1.970 |
| CPI | 3.624 | 2.719 | 0.145 | 3.054 | 0.192 | 1.741 | 0.299 | 0.346 | 0.375 | 1.254 | 1.075 | 1.067 | 1.444 | 1.147 | 1.838 | 1.270 | 1.238 | 1.423 | 1.984 |
| INDPRO | 85.858 | 2.211 | 2.135 | 1.221 | 4.619 | 0.803 | 2.238 | 1.155 | 22.557 | 1.525 | 1.079 | 1.039 | 1.320 | 1.151 | 1.668 | 1.301 | 1.183 | 1.410 | 1.934 |
| M1 | 0.005 | 0.454 | 1.216 | 0.112 | 1.451 | 2.539 | 0.481 | 5.482 | 0.598 | 2.997 | 1.091 | 1.073 | 1.412 | 1.153 | 1.813 | 1.237 | 1.232 | 1.389 | 1.970 |
| UNRATE | 123.275 | 14.625 | 2.055 | 5.984 | 4.207 | 0.779 | 3.033 | 2.669 | 0.366 | 1.718 | 1.062 | 1.049 | 1.341 | 1.124 | 1.731 | 1.296 | 1.159 | 1.391 | 1.994 |
| | 64.231 | 13.061 | 2.720 | 13.241 | 3.923 | 1.273 | 3.657 | 0.928 | 1.549 | 1.802 | 1.180 | 1.166 | 1.483 | 1.236 | 1.638 | 1.477 | 1.294 | 1.464 | 1.868 |
| USDAUS | | | | | | | | | | | | | | | | | | | |
| USDINR | 1.504 | 2.628 | 3.189 | 7.945 | 3.367 | 1.957 | 2.749 | 1.299 | 0.553 | 2.164 | 1.223 | 1.166 | 1.643 | 1.273 | 1.691 | 1.597 | 1.387 | 1.443 | 1.927 |
| AR(1) | 3.268 | 2.704 | 1.347 | 2.510 | 1.419 | 0.206 | 1.620 | 2.495 | 1.328 | 1.096 | 1.063 | 1.047 | 1.293 | 1.127 | 1.707 | 1.362 | 1.122 | 1.403 | 1.965 |

This table displays (i) the ratios of slope coefficient estimates for recession periods versus expansions, $\beta = \hat{\beta}^2_{\text{Rec}}/\hat{\beta}^2_{\text{Exp}}$; (ii) the ratios of the variance of $x_t$ (the predictor) in recessions and expansions, $\sigma_x^2 = \sigma^2_{x,Rec}/\sigma^2_{x,Exp}$; and (iii) the ratios of the variances of the residuals in recessions and expansions, $\sigma_\epsilon^2 = \hat{\sigma}^2_{\epsilon,Rec}/\hat{\sigma}^2_{\epsilon,Exp}$. The results are computed using the full sample of monthly data, 1947–2010.

**Table 7**
Forecasting performances in recessions versus expansions.

| | Fats/oils | Foods | Industrials | Livestock | Metals | Textiles | Commodity | Stock | Bond |
|---|---|---|---|---|---|---|---|---|---|
| Slope | 100.000 | 100.000 | 91.666 | 100.000 | 100.000 | 100.000 | 100.000 | 91.666 | 91.666 |
| Predictor variance | 75.000 | 83.333 | 83.333 | 75.000 | 75.000 | 58.333 | 66.666 | 66.666 | 33.333 |
| Residuals variance | 16.666 | 8.333 | 8.333 | 16.666 | 16.666 | 33.333 | 25.000 | 25.000 | 58.333 |

This table displays the proportion of univariate predictors for which we observe (i) $_{R^2}$ and $_{\beta}$ both greater than one, as measured by Slope $= \frac{1}{K}\sum_{1=1}^{K} I(\ _{R^2} > 1) * I(\ _{\beta} > 1)$; (ii) $_{R^2}$ and $_{\sigma_x^2}$ both greater than one, as measured by Predictor variance $= \frac{1}{K}\sum_{i=1}^{K} I(\ _{R^2} > 1) * I(\ _{\sigma_x^2} > 1)$; and (iii) $_{R^2}$ greater than one and $_{\sigma_\epsilon^2}$ smaller than one, as measured by Residuals variance $= \frac{1}{K}\sum_{i=1}^{K} I(\ _{R^2} > 1) * I(\ _{\sigma_\epsilon^2} < 1)$. In these formulas, $I(\circ)$ is an indicator function taking the value of one if its argument is true and zero otherwise, and $K$ is the total number of predictors. The results are computed using the full sample of monthly data, 1947–2010.

(absolute) magnitude of the regression coefficients, $\beta$; and (iii) increasing with the variances of the individual predictors, $\sigma_x^2$. To measure the separate effects of these three sources, we estimate two predictive regressions, one for expansions and one for recessions, using the recession indicator in Eq. (9) to determine the state:

$$r_{t+1} = \begin{cases} \alpha_{rec} + \beta_{rec} x_t + \epsilon_{t+1}\epsilon_{t+1} \sim N(0, \sigma^2_{\epsilon,rec}) \\ \text{if in recession: } \tilde{U}_t > 0.5, \\ \alpha_{\exp} + \beta_{\exp} x_t + \epsilon_{t+1}\epsilon_{t+1} \sim N(0, \sigma^2_{\epsilon,\exp}) \\ \text{if in expansion: } \tilde{U}_t = 0. \end{cases}$$

Using these regressions, we first compute the ratio of the $R^2$ values in recessions and expansions, $_{R^2} = R^2_{rec}/R^2_{\exp}$. Values of $_{R^2}$ above (below) one suggest that predictability is higher (lower) in recessions than in expansions.

We next compute the ratio of the squared value of $\hat{\beta}$ in recessions and expansions, $_{\beta} = \hat{\beta}^2_{rec}/\hat{\beta}^2_{\exp}$. Values of $_{\beta}$ above one suggest that the slope coefficients tend to increase during recessions. We also compute the ratio of the variance of the residuals in recessions and expansions, $_{\sigma_\epsilon^2} = \hat{\sigma}^2_{\epsilon,rec}/\hat{\sigma}^2_{\epsilon,\exp}$. Values of $_{\sigma_\epsilon^2}$ above one suggest that the residual variance tends to increase during recessions. Finally, we compute the ratio of the variance of $x_t$ in recessions and expansions, $_{\sigma_x^2} = \sigma^2_{x,rec}/\sigma^2_{x,\exp}$. Values of $_{\sigma_x^2}$ above one suggest that the variance of the predictors increases during recessions.

Table 6 shows the results from these calculations, which are only undertaken for the monthly data, since the recession indicator is less well defined at the quarterly and annual horizons. Interestingly, we find that all three measures tend to increase during recessions. In recessions, the slope coefficients increase, the variances of the predictor variables increase, and the residual variance also increases. However, the residual variances tend to increase for fewer of the predictors and by smaller amounts than the corresponding increases in the slope coefficients and predictor variances. The net effect is for the predictive $R^2$ to increase during recessions.

Values of $_{R^2} = R^2_{rec}/R^2_{\exp}$ above one (increases in predictability) require a positive $_{\beta}$ (an increase in the regression coefficients), or a positive $_{\sigma_x^2}$ (an increase in the variance of the predictors), or a negative $_{\sigma_\epsilon}$ (a decrease in the variance of the residuals), or some combination of these. For each commodity index, we compute the fraction of predictors for which we observe $_{R^2}$ and $_{\beta}$ above one:

$$\text{Slope} = \frac{1}{K}\sum_{k=1}^{K} I(\ _{R^2,k} > 1) I(\ _{\beta,k} > 1);$$

$_{R^2}$ and $_{\sigma_x^2}$ above one:

$$\text{Predictor\_variance} = \frac{1}{K}\sum_{k=1}^{K} I(\ _{R^2,k} > 1) * I(\ _{\sigma_x^2,k} > 1);$$

and values of $_{R^2}$ above one and $_{\sigma_\epsilon^2}$ below one:

$$\text{Residual\_variance} = \frac{1}{K}\sum_{k=1}^{K} I(\ _{R^2,k} > 1) * I(\ _{\sigma_\varepsilon^2,k} < 1).$$

Here, $I(\circ)$ is an indicator function that takes a value of one if its argument is valid, and is zero otherwise.

The results, reported in Table 7, show that, for most predictors, higher slope coefficients contribute to the increased $R^2$ values observed during recessions, as do increased levels of variability in the predictors. In contrast, there are few cases in which the volatility of the residuals decreases during recessions.

These findings suggest that the predictability of commodity prices is highly state dependent. Recessions are periods in which more predictor variables possess predictive power over commodity prices relative to expansions. This higher predictability arises due to both larger slope coefficients and higher levels of variability in the predictor variables, and happens in spite of the increased variance of the unpredictable shocks to commodity prices during economic recessions.

## 6. Conclusion

Using spot price data on a sample of commodity indexes over the period 1947–2010, we examine the predictability of commodity price changes at the monthly, quarterly, and annual horizons. Overall, we find that the out-of-sample predictability of commodity prices is strongest at the quarterly horizon, but that it varies considerably across different commodity price indexes, being strongest for industrials, metals, and the broad commodity index, and weaker for fats/oils, foods, and livestock.

We also find that commodity price predictability is closely linked to the economic cycle. Commodity prices are most predictable during recessions, due partly to higher slope coefficients in predictive return regressions, and partly to the higher variability of macroeconomic and financial variables during recessions. This is in spite of a concomitant increase in the variance of the unpredictable component of commodity prices during recessions.

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## References

Acharya, V. V., Lochstoer, L. A., & Ramadorai, T. (2011). *Limits to arbitrage and hedging: evidence from commodity markets*. Unpublished discussion paper.

Alquist, R., & Kilian, L. (2010). What do we learn from the price of crude oil futures? *Journal of Applied Econometrics*, *25*, 539–573.

Bessembinder, H., & Chan, K. (1992). Time-varying risk premia and forecastable returns in futures markets. *Journal of Financial Economics*, *32*, 169–193.

Chen, Y., Rogoff, K., & Rossi, B. (2010). Can exchange rates forecast commodity prices? *Quarterly Journal of Economics*, *125*, 1145–1194.

Clark, T. E., & West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics*, *138*, 291–311.

Croushore, D., & Stark, T. (2001). A real-time data set for macroeconomists. *Journal of Econometrics*, *105*, 111–130.

De Mol, C., Giannone, D., & Reichlin, L. (2008). Forecasting with a large number of predictors: is Bayesian regression a valid alternative to principal components? *Journal of Econometrics*, *146*, 318–328.

Elliott, G., Gargano, A., & Timmermann, A. (2013). Complete subset regressions. *Journal of Econometrics*, *177*, 357–373.

Goyal, A., & Welch, I. (2008). A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies*, *21*, 1455–1508.

Groen, J. J. J., & Pesenti, P. A. (2011). Commodity prices, commodity currencies, and global economic developments. In T. Ito, & A. Rose (Eds.), *Commodity prices and markets, East Asia Seminar on Economics, Vol. 20* (pp. 15–42). Chicago: University of Chicago Press.

Henkel, S. J., Martin, J. S., & Nardari, F. (2011). Time-varying short-horizon predictability. *Journal of Financial Economics*, *99*, 560–580.

Hong, H., & Yogo, M. (2012). What does futures market interest tell us about the macroeconomy and asset prices? *Journal of Financial Economics*, *105*, 473–490.

Inoue, A., & Killian, L. (2008). How useful is bagging in forecasting economic time series? A case study of US consumer price inflation. *Journal of the American Statistical Association*, *103*, 511–522.

Kilian, L. (2009). Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. *American Economic Review*, *99*(3), 1053–1069.

Rapach, D. E., Strauss, J. K., & Zhou, G. (2010). Out-of-sample equity premium prediction: combination forecasts and links to the real economy. *Review of Financial Studies*, *23*, 821–862.

Stock, J. H., & Watson, M. W. (2010). Modeling inflation after the crisis. Presented at the *FRB Kansas city symposium on macroeconomic policy: post-crisis and risks ahead*, Jackson Hole, Wyoming.