Commodity prices, commodity currencies, and global economic developments*

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Abstract

In this paper we seek to produce forecasts of commodity price movements that can systematically improve on naive statistical benchmarks, and revisit the forecasting performance of changes in commodity currencies as efficient predictors of commodity prices, a view emphasized in the recent literature. In addition, we consider different types of factor-augmented models that use information from a large data set containing a variety of indicators of supply and demand conditions across major developed and developing countries. These factor-augmented models use either standard principal components or partial least squares (PLS) regression to extract dynamic factors from the data set. Our forecasting analysis considers ten alternative indices and sub-indices of spot prices for three different commodity classes across different periods. We find that the exchange rate-based model and especially the PLS factor-augmented model are more prone to outperform the naive statistical benchmarks. However, across our range of commodity price indices we are not able to generate out-of-sample forecasts that, on average, are systematically more accurate than predictions based on a random walk or autoregressive specifications.

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JEL Classification: C23, C53, F47

1 Introduction

In a June 2008 speech, significantly titled "Outstanding Issues in the Analysis of Inflation", Federal Reserve Chairman Bernanke [3] singled out the role of commodity prices among the main drivers of price dynamics, "underscoring the importance for policy of both forecasting commodity price changes and understanding the factors that drive those changes". While inflationary pressures were very much in the minds of monetary policymakers across the globe at that time, the macroeconomic outlook changed rapidly and dramatically in the months following the speech, as the global economy experienced the near-collapse of trade volumes and the associated plunge in commodity prices was the harbinger of pervasive disinflation risks. During the second half of 2009 the signs of an approaching recovery did re-emerge worldwide. At the time of this writing (end 2009) a rally in commodity prices, once again, is resurrecting inflationary threats.

Are they justified? Are they premature? The answers to these questions depend on a long list of variables, and are subject to many caveats. First, pass-through of commodity price swings to final retail prices takes time; IMF [25] reports estimates of an average propagation lag of about 9-12 months for the transmission of oil price shocks, and up to 30 months for the transmission of food price shocks. Second, intensity of use affects a country's CPI vulnerability to commodity price swings. For instance, energy intensity is typically lower in advanced economies than in emerging and developing countries, and food expenditure represents over one-third of consumption in emerging economies, but only one tenth of consumption in advanced economies. Third, monetary policy credibility matters. Under regimes of high credibility, changes in the prices of oil, industrial metals and agricultural commodities can have a significant impact on headline inflation without unmooring medium-term inflation expectations. But expectations under weak policy credibility depend on current and past inflation, enhancing the impact of commodity price shifts on core inflation. Fourth, exchange rates can amplify or mitigate the transmission mechanism, as commodities are typically priced in dollars, while retail prices are denominated in local currencies (according to IMF [25], a 1 percent effective dollar depreciation raises oil prices in dollars by more than 1 percent).[1]

More than anything, the link between commodity price cycles and inflation is bound to be affected by the size and persistence of commodity price movements, and in this respect, recent swings in commodity prices have been nothing short of spectacular. Following large increases between 2003 and 2006, oil prices accelerated and more than doubled between

[1] See also Keyfitz [26] and Verleger [33].

the end of 2006 and the time of the aforementioned Bernanke speech. Food prices rose by about 50 percent over the same time horizon, with particularly rapid trajectories for corn, wheat, rice and soybeans. To find traces of a comparable boom one has to go back to the early 1970s, as no major commodity cycle materialized during the 1980s or the 1990s. The subsequent price bust in late 2008 was just as dramatic as this most recent pick-up. Between July 2008 and February 2009, energy prices collapsed by 70 percent, and agricultural prices by 37 percent.[2]

Long-term trends in fundamentals, slower population growth and weaker global income and output growth suggest that the recent peaks are unlikely to be the new norm (see World Bank [34]). But what will come next is by no means an easy prediction — which is precisely the key message of the current contribution.

The 'easy way out' of relying on commodity futures as signals of future spot price movements is, in practice, highly inadequate.[3] A long literature emphasizes that commodity price dynamics are influenced in theory and in practice by a large variety of factors, including but not limited to growth in large emerging economies, inventory and supply constraints, monetary and exchange rate policies, and possibly financial speculation. Section 2 of this paper provides a succinct summary of the different arguments. In light of these considerations, the search for a comprehensive approach to forecasting is bound to be quixotic. Nevertheless, a recent paper by Chen, Rogoff and Rossi [8] (hereinafter CRR) appears to provide a pragmatic Ariadne's thread to approach the maze.

According to CRR, exchange rate fluctuations of relatively small commodity-exporting countries such as Canada, Australia, New Zealand, Chile and South Africa with market-based floating exchange rates have "remarkably robust power in predicting future global commodity prices." While the basic notion that changes in commodity currencies are correlated with commodity prices is not new in the literature, CRR provides a systematic attempt to document and test the forecasting properties of a small set of commodity currencies as explanatory variables, with surprisingly promising results both in-sample (using Granger-causality tests robust to parameter instabilities) and out-of-sample.

The results from CRR [8] are the direct motivation for our contribution. The basic idea is to take a broad index of different spot commodity prices as the forecast variable (we consider ten alternative indices and sub-indices for three different commodity classes), and compare the forecasting properties of three approaches against a baseline autoregressive or random

[2] On the links between commodity prices and inflation see also Cecchetti and Moessner [7] and Hobijn [22].

[3] See the paper by Chan, Tse and Williams in this volume for a recent assessment.

walk process. The three approaches include a model in which forecasts are based only on the information embedded in observed past movements of commodity currencies, as in CRR, and two variants of a factor-augmented regression model that makes use of information from a relatively large data set, as described below. The purpose of our exercise is ultimately to provide an agnostic but reasonably systematic look at the global roots of commodity price dynamics. Rather than attempting to answer questions such as “why are commodity prices so high or so low ”and “how long are they going to stay where they are”, our contribution has the more modest purpose of providing an empirical assessment of the extent to which information embedded in indicators of global economic developments may help in predicting movements of commodity prices, by improving upon the naive statistical benchmarks or the CRR approach.

The main conclusions of the paper can be summarized as follows. We are able to provide some corroboration, albeit rather mild, for the CRR results. For one specific commodity index, at the shortest forecasting horizons (up to one-quarter ahead), the predictions of an exchange rate-based model are significantly better than those based on a random walk, although they do not outperform an autoregressive specification; at the one-year ahead horizon, the performance is reverted, as the CRR model significantly outperforms the autoregressive benchmark but not the random walk. When other indices are considered, the results are nuanced. We also find that a model encompassing principal components extracted from a panel of global economic explanatory variables generally performs poorly. We obtain more promising results when we replace the principal components approach with a different methodology (a partial least squares factor-augmented model), suggesting that information from a larger set of macrovariables can have some predictive power. However, across commodity indices we cannot generate forecasts that are, on average, structurally more accurate and robust than those based on a random walk or autoregressive specifications.

The paper is organized as follows. Section 2 provides a synthetic survey of the different arguments used to rationalize and predict shifts in commodity prices. Section 3 describes the methodology used in constructing our exchange rate-based and factor-augmented regression models and assessing their forecasting properties against the naive statistical benchmarks. Section 4 reports and discusses our results. Section 5 concludes.

2 Interpreting commodity price cycles

In retrospect, and with the advantage of hindsight, one can always attempt to rationalize movements of commodity prices in terms of supply and demand fundamentals.[4] Taking for instance the case of oil prices, Hamilton [20] emphasizes that, while historical oil price shocks were primarily caused by physical disruptions of supply, the price run-up of 2007-08 was caused by strong demand confronting stagnating world production and little spare capacity.[5] A mismatch between fast demand growth and increasing intensity of GDP in countries such as China on the one hand,[6] and slow-growing supply capacity due to sluggish investment until the early 2000s on the other hand, similarly explains the path of industrial metals (see [34]). As far as food prices were concerned, weather shocks and supply bottlenecks certainly played a role in the recent cycle. But the decline in global inventory in the mid-2000s was mainly the result of strong growth of consumption in emerging and developing economies. Also, attempts to avoid the consequences of rising fuel prices by exploring alternative sources of energy led governments to revise their biofuel mandates and subsidize production. The outcome was soaring demand for corn and some vegetable oils. Because of corn-based ethanol production in the U.S., about 30 percent of the entire corn crop was diverted toward production of biofuels (see [25]).[7]

Understanding long-run trend movements in fundamentals, however, does little to enhance our ability to predict the extent, persistence, or volatility of changes in short-term supply and demand, nor their effects on commodity prices. Take once again the case of oil. The argument can be made that increasing extraction costs in marginal fields imply that future capacity will be built at higher costs. At the same time, short-term demand price elasticity is likely to remain rather low (below 0.1 according to most estimates), even though income elasticities are somewhat higher.[8] As a result, small revisions in the expected

[4] Structural macroeconomic fundamentals were emphasized in early papers on the determination and forecasting of commodity prices such as Reinhart [28] and Borensztein and Reinhart [5].

[5] Kilian [27] downplays the contribution of current supply disruptions to price movements, attributing fluctuations in the price of oil to "precautionary demand associated with market conditions about the availability of future oil supplies".

[6] Currently GDP metal intensity in China is four times higher than in developed countries. Going forward, China's metal intensity is expected to peak and move closer to the world's average (see [34]).

[7] Going forward, even assuming that food demand will slow with lower population growth and strong productivity growth will ensure adequate food supply, biofuels could expand demand rapidly, with associated upside risks for corn prices (see [34]).

[8] The price elasticity may be time varying. For instance, in the early part of the past decade the initial response of U.S. consumers to oil price increases was relatively muted due, among other factors, to the low share of gasoline in consumption spending. By 2007-8 energy had returned to an importance for a typical budget not seen since the 1970s, enhancing the sensitivity of consumers' behaviors to bad news about energy prices (see [20]).

path of future supply expansion can have large and highly volatile effects on expected future prices. Heuristically, one can understand the difficulties related to predicting oil price changes by visualizing the market for oil as the overimposition of a virtually vertical line (inelastic demand) with another vertical line (inelastic supply). While the quantity traded is not in doubt, the equilibrium price in such market is very much in the eye of the beholder. Minor movements of either curves, related to small adjustments in inventories or marginal changes in extraction decisions, can have sizable (and unpredictable) effects on prices.[9] Similar considerations may apply, *ceteris paribus*, to other commodity classes.

The extent and volatility of recent swings have prompted some observers to dismiss attempts to rationalize and predict commodity price movements in terms of fundamentals, and focus instead on the role of other factors such as speculative behaviors in the futures markets. The basic idea is that speculative strategies that drive futures prices up must be reflected in higher spot prices today regardless of long-term fundamentals, or agents would have an incentive to accumulate inventories which could be sold later at higher prices. More generally, commodity prices are forward-looking variables that reflect and process expectations about future price changes. The effects of speculative and forward-looking behaviors are likely to be stronger in an environment of rapid declines in short-term interest rates, lowering the opportunity cost of physical commodity holding as emphasized by Frankel [15], and prompting investors in money-market instruments to seek higher yields in alternative asset classes such as commodity futures. In this light, very rapid declines of short-term rates in early 2008 may have "fanned the flames of commodity speculation" as Hamilton [20] puts it.[10]

The jury is still out on whether speculation can effectively drive spot prices. A 2008 report of the Interagency Task Force on Commodity Markets [24] did not find speculation behind higher oil prices: if anything, speculators tended to react *after*, rather than in anticipation of, price changes. Skeptic rebuffs of the speculation theory point out that speculation in the futures market can raise spot prices to the extent that it is accompanied by increasing physical hoarding. But there is no systematic inventory hoarding evidence in recent episodes of high volatility in spot commodity prices. If anything, oil inventories were moving downward, not upward at the time of sharpest price movements, suggesting that inventory changes served to mitigate rather than aggravate the magnitude of oil price

[9] The observed large volatility in the rate of change of non-renewable minerals and fossil fuels, as well as the absence of long-term positive trends makes it difficult to reconcile the empirical evidence with the prescriptions of the Hotelling's rule [23]. According to this rule, the price of non-renewable resources should be growing continuously at a rate that tends towards the rate of interest as the share of cost in price gets smaller and smaller over time. For a recent assessment see Gauded [16].

[10] See also Akram [1].

shocks (see [24]). A related mechanism linking futures and spot prices requires current production to be foregone (including the deliberate choice to keep oil in the ground) in response to anticipated higher future prices. The fact is that, to rationalize a speculation-based interpretation of the oil shocks of 2007-08, one needs a combination of two elements: low price elasticity of demand and failure of physical production to increase. But these are precisely the two key ingredients of a fundamentals-only explanation as pointed out by Hamilton [20], so that, ultimately, the two approaches are observationally equivalent.[11]

One could argue that, regardless of speculation, futures prices should help to predict the direction of future price movements, as they efficiently incorporate information available to market participants. But futures prices provide, at best, highly noisy signals about future spot prices.[12] The difference between the futures price and the current spot price (or futures basis) is not in itself an indicator of the expected direction of change of spot commodity prices, as it reflects both the expected decline in the spot price and a risk premium. Gorton and Rouwenhorst [19] suggest that the basis "seems to carry important information about the risk premium of individual commodities", somewhat downplaying the role of market expectations about the expected spot return. Also, it is unclear whether prices in relatively illiquid segments of the futures market such as longer-dated contracts can be considered unbiased and effective aggregators of information.

A different — and more promising — approach exploits the forward-looking nature of a different category of asset prices, namely exchange rates. As shown forcefully by Engel and West [14], bilateral exchange rates between any pair countries reflect expectations about future changes in the underlying relative economic fundamentals. Therefore, exchange rates of predominantly commodity-exporting economies *vis-à-vis*, say, the U.S. should reflect expectations about demand and supply conditions in world commodity markets. This is the rationale for the finding by CRR [8] that commodity exchange rates can be remarkably effective predictors of future commodity prices. CRR observe that primary commodity products represent a key component of output in the five commodity-exporting countries under consideration, affecting a large fraction (between 25 and more than 50 percent) of their export earnings. At the same time these countries are too small to have monopoly power on international relative prices through the manipulation of the supply of their exports, so that global commodity price changes end up representing sizable term of trade shocks for these countries. Market expectations of these changes are priced into current exchange rates, through standard forward-looking mechanisms. Ultimately, observable movements in

[11] See also Slade and Thille [30].

[12] For a survey of the evidence see Bowman and Husain [6].

a small number of exchange rates embed valuable information on the direction of change of future commodity prices, making commodity currencies significantly better predictors than standard approaches based on traditional statistical models (such as a random walk or a mean-reverting autoregressive process).

In light of the above considerations, a pragmatic approach to commodity prices forecasting is to use information from a large variety of indicators of supply and demand conditions across major developed and developing countries, complementing the forecasting power of commodity currencies with the one embedded in current global economic developments. The set of macro-economic time series we consider includes industrial production, business and consumer confidence data, retail sales volumes, unemployment rates, core consumer prices (excluding food and energy), money aggregates and interest rates, as well as data on inventories and production of industrial metals, oil, natural gas and coal, and more unusual variables such as the Baltic Dry Index (BDI) — an index which captures the average price of ocean shipping, aggregating prices of many different routes and types of shipping vessels. The complete list of variables we consider can be found in the Data Appendix.

3 Methodological issues

3.1 Three specifications of the forecasting equation

Turning now to the formal aspects of our exercise, in what follows we focus on the performance of direct forecasts from fundamentals-based regressions for a number of commodity price indices.[13] Following standard practice in the forecasting literature, we use an autoregressive (AR) model as the forecasting benchmark for such regressions. The *AR benchmark model* in the context of direct forecasting can be written as:

$$\Delta p_{t+h,t} = \alpha^h + \sum_{i=1}^{k} \rho_i \Delta p_{t-i+1,t-i} + \epsilon_{t+h,t}, \quad t = 1, \dots, T \tag{1}$$

where $p_t = \ln(P_t)$ and P_t is a spot commodity price index, $\Delta p_{t+h,t} = p_{t+h} - p_t$ for the forecasting horizon $h > 0$, and $\Delta p_{t-i+1,t-i} = p_{t-i+1} - p_{t-i}$ for $i = 1, \dots, k$. The number of lagged first differences k in (1) is determined by sequentially applying the standard Schwarz [29] Bayesian information criterion (BIC) starting with a maximum lag order of $k = k_{max}$ down to $p = 1$. The unconditional mean benchmark is simply:

$$\Delta p_{t+h,t} = \alpha^h + \epsilon_{t+h,t}, \tag{2}$$

[13] While the time-series reduced-form approach of the paper provides a simple and flexible framework for our forecasting exercise, it sacrifices the information embedded in a medium- or large-scale econometric model. As an example of a stochastic dynamic general-equilibrium model dealing with the transmission of commodity prices in the global economy, see [13].

which implies a *random walk (RW) forecast* for the level of the forecast variable p_t.

The benchmark models in (1) and (2) use solely the information embedded in the commodity price time series itself. However, when forecasting commodity price changes, it might be useful to incorporate information from additional, theoretically relevant, variables. For instance, CRR [8] explore the usefulness of exchange rates to predict commodity prices. Consistently, we follow CRR [8] and modify (1) by adopting the following specification for the *exchange rate-based model*:

$$\Delta p_{t+h,t} = \alpha^h + \sum_{m=1}^{M} \gamma_m \Delta e_t^m + \sum_{i=1}^{k} \rho_i \Delta p_{t-i+1,t-i} + \epsilon_{t+h,t}. \tag{3}$$

In (3) $\Delta e_t^1, \ldots, \Delta e_t^M$ are the first differences of the log U.S. dollar exchange rates of M commodity-exporting economies.

More generally, from a forecasting vantage point it might be useful to exploit information from a set of economically relevant variables not limited to commodity exchange rates. For this purpose, *factor-augmented regressions* provide a convenient approach. One seminal application of the use of factor-augmented regressions is Stock and Watson [32], where a limited number of principal components extracted from a large data set are added to a standard linear regression model, that is then used to forecast key macroeconomic variables. Stock and Watson [31] and Bai [2] formalized the underlying asymptotic theory, which allows the use of principal components to identify the common factors in very large data sets. Our factor-augmented regressions adhere to the following specification:

$$\Delta p_{t+h,t} = \alpha^h + \sum_{i=1}^{r} \beta_i^h f_{i,t}^{PC} + \sum_{j=1}^{k} \rho_i \Delta p_{t-j+1,t-j} + \epsilon_{t+h,t}. \tag{4}$$

Following Stock and Watson [32] we take a $T \times N$ matrix of N indicator variables, say $X = (x_1' \cdots x_T')'$, and normalize X such that the variables are in zero-mean and unity variance space, which results in the $T \times N$ matrix $\tilde{X}$. We then compute the r eigenvectors of the $N \times N$ matrix $\tilde{X}'\tilde{X}$ that correspond to the first $\hat{r}$ largest eigenvalues of that matrix. By post-multiplying $\tilde{X}$ with these eigenvectors we obtain the estimated factors $f_{i,t}^{PC}$ used in (4).

The drawback of the aforementioned factor-augmented regression approach is that the use of principal components does not always guarantee that the information extracted from a large number of predictors is particularly useful in the context of the specific forecasting exercise. Boivin and Ng [4] make it clear that if the forecasting power comes from a certain factor, this factor can be dominated by other factors in a large data set, as the principal components solely provide the best fit for the large data set and not for the target variable of interest. We therefore consider an alternative to principal components in which only the factors relevant for modeling the target variable, commodity price changes in our case, are extracted from the predictor variable set. One possible approach is partial least squares (PLS) regression. As Groen and Kapetanios [17] show, PLS regression outperforms the usual principal components-based approach both in simulations and empirically, and especially when the underlying factor structure is weak.[14]

We implement PLS regression by constructing the factors as linear, orthogonal combinations of the (normalized) predictor variables assembled in the $T \times N$ matrix $\tilde{X} = (\tilde{x}_1' \cdots \tilde{x}_T')'$, such that the linear combinations maximize the covariance between the h-period ahead commodity price changes and each of the common components constructed from the predictor variables. In practice, we specify the corresponding *factor-augmented regression model* as:

$$\Delta p_{t+h,t} = \alpha^h + \sum_{i=1}^{r} \beta_i^h f_{i,t}^{PLS} + \sum_{j=1}^{k} \rho_i \Delta p_{t-j+1,t-j} + \epsilon_{t+h,t}, \tag{5}$$

where the PLS factors are extracted according to a similar scheme as in Groen and Kapetanios [17], namely:

1. Demean $\Delta p_{t+h,t}$ resulting in $\Delta\tilde{p}_{t+h,t}$ and set $u_t = \Delta\tilde{p}_{t+h,t}$ and $v_{i,t} = \tilde{x}_{l,t}$, $l = 1, ...N$. If lagged price changes are included in (5), regress both $\Delta\tilde{p}_{t+h,t}$ as well as the $\tilde{x}_{l,t}$'s on $\Delta p_{t-j+1,t-j}$ for $l = 1, \ldots, N$ and $j = 1, \ldots, k$.[15] Denote the resulting residuals as $\Delta\check{p}_{t+h,t}$ and $\check{x}_{l,t}$'s $l = 1, \ldots, N$. Set $u_t = \Delta\check{p}_{t+h,t}$ and $v_{i,t} = \check{x}_{l,t}$, $l = 1, ...N$. Finally, set $i = 1$.

2. Determine the $N \times 1$ vector of loadings $w_i = (w_{1i} \cdots w_{Ni})'$ by computing individual covariances: $w_{li} = Cov(u_t,\ v_{it})$, $l = 1, ..., N$ and $t = 1, \ldots, T - h$. Construct the i-th PLS factor by taking the linear combination given by $w_i' v_t$ and denote this factor by $f_{i,t}^{PLS}$.

3. Regress u_t and $v_{l,t}$, $l = 1, ..., N$, $t = 1, \ldots, T - h$ on $f_{i,t}^{PLS}$. Denote the residuals of these regressions by $\tilde{u}_t$ and $\tilde{v}_{l,t}$ respectively.

4. If $i = r$ stop, else set $u_t = \tilde{u}_t$, $v_{l,t} = \tilde{v}_{l,t}$ $l = 1, .., N$ and $i = i + 1$ and go to step 2.

[14] One condition under which principal components provide consistent estimates of the unobserved factor structure in a large data set is when these factors strongly dominate the dynamics of the series in such a data set relative to the non-factor components of the data (see, e.g., Bai [2]). However, in practice the factors might not dominate the non-structural dynamics as strongly as assumed in the underlying asymptotic theory. This affects the accuracy of the factors estimated through principal components. PLS regression, on the other hand, yields consistent factor estimates even in the latter case — see [17].

[15] As the weights (also known as loadings) of the predictor variables in each of the constructed PLS factors depend on the covariance of these with commodity price changes, the inclusion of lagged commodity price changes will affect these loading estimates.

Selecting the optimal number of factors in the aforementioned factor-augmented regression approaches is a crucial issue, as is the optimal lag order. Moreover, this selection process is complicated by the fact the factors in (4) and (5) are generated regressors. In finite samples, the estimation error from a generated regressor adds to the overall estimation error variance in a regression. So in determining whether to include a regressor one should balance in the standard case the increase in goodness of fit with adding the noise of an extra free parameter, whereas in the case of a generated regressor the trade-off is between improvement of fit and adding noise of *both* an extra parameter and an extra, estimated, variable. The latter model selection problem rules out the usage of standard measures such as BIC. Instead, in the cases of (4) and (5) we adopt the factor- and lag-order selection criterion as proposed in Groen and Kapetanios [18]. The following information criterion is valid for both regressions (4) and (5) under the framework spelled out in Theorem 2 of [18]:

$$BICM = \frac{T}{2}\ln\{\hat{\sigma}^2_{\hat{\epsilon}}\} + (1+k)\ln(T) + r\ln(T)\left(1+\frac{T}{N}\right), \tag{6}$$

where $\hat{\sigma}_{\hat{\epsilon}}$ is the standard OLS variance estimator. The third right hand side term in the $BICM$ measure above is a penalty term for adding the estimated factors to regressions (4) and (5). This term is motivated by the result that, when in the underlying panel of predictor variables the dimensions T and N go to infinity, the factors become observed. Therefore, the dimensions of this underlying panel determine the penalization for the number of factors in finite samples. Hence, searching for the optimal values of the modified IC in (6) provides the econometrician with a consistent, simultaneous, estimate of the optimal values of r and k in regression (4) and (5).

3.2 Assessing the forecasting properties

Before we proceed we need to deal with the realistic possibility that the dynamics of the forecasting variable (commodity prices in our case) has not been stable over time. Our approach is to update the forecasting models based on a fixed rolling window of historical data encompassing ω periods. In detail, the steps are as follows:

1. For any given forecast horizon h, the first forecast is generated on $t_0 = \omega$.

2. Extract r^{max} principal components and PLS factors from the N predictor variables over the sample $t = t_0 - \omega + 1, \ldots, t_0 - h$.

3. Determine over the sample $t = t_0 - \omega + 1, \ldots, t_0 - h$ the optimal lag order and optimal number of factors in both (4) and (5) for our criterion BICM (see (6)) across the range $j = 0, \ldots, k^{max}$ and $i = 1, \ldots, r^{max}$. This results in $(\hat{k}^{PC}_{BICM}, \hat{r}^{PC}_{BICM})$ and

$(\hat{k}^{PLS}_{BICM}, \hat{r}^{PLS}_{BICM})$. In a similar vein, determine also the optimal lag order for the AR benchmark (1) and the exchange rate-based model (3) based on BIC.

4. Given the outcome of step 3, estimate (1)-(5) over the sample $t = t_0 - \omega + 1, \ldots, t_0 - h$ for each h.

5. Extract r^{max} principal components and PLS factors from the N predictor variables over the sample $t = t_0 - \omega + 1, \ldots, t_0$.

6. Generate the forecast $\Delta\hat{p}_{t+h,t}$ using the estimated dimensions from step 3 and the parameter estimates from step 4 as well as, in case of (4) and (5), the factors from step 5.

7. Repeat for $t_0 + 1, \ldots, T - h$ and for any forecast horizon h.

To assess the forecasting performance of the respective models we consider the mean of the squared forecast errors [MSE]:

$$\text{MSE} = \frac{1}{T - t_0 - h} \sum_{s=t_0}^{T-h} \varepsilon^2_{s,s+h}, \tag{7}$$

where $\varepsilon_{s,t+h}$ is the forecast error of the model-generated prediction of the commodity price change, based on the previously described recursive updating scheme, relative to the *observed* commodity price change over h periods. It is, however, questionable whether one should compare the 'raw' MSE (7) of the fundamentals-based predictions, i.e. those based on (3), (4) or (5) (denoted as MSE_F), with the MSE of our, more parsimonious, benchmark models (labeled as MSE_B. Clark and West [9, 10] show both theoretically as well as in Monte Carlo simulations that $\text{MSE}_\text{RW} - \text{MSE}_\text{F}$ or $\text{MSE}_\text{AR} - \text{MSE}_\text{F}$ is biased downwards as MSE_F is inflated by spurious noise as the result of inappropriately fitting a larger model on the data. Asymptotically this spurious noise in MSE_F disappears, but it can be quite pervasive in finite samples, especially in the case of (4) and (5) where the factors have to be estimated first before a forecast can be constructed. Thus, for sample sizes comparable to those used in practice, tests based on 'raw' MSE differentials relative to (1) or (2) are severely undersized, which makes it harder to find any evidence against the benchmark forecast.

Following Clark and West [9, 10], we compare the MSE (7) based on either (1) or (2) with corrected MSE measures for (3), (4) and (5), i.e.,

$$\text{MSE}^{adj}_\text{F} = \text{MSE}_\text{F} - \left(\frac{1}{T - t_0 - h} \sum_{s=t_0}^{T-h} \left(\Delta\hat{p}^\text{B}_{s,s+h} - \Delta\hat{p}^\text{F}_{s,s+h} \right)^2 \right); \quad \text{B} = \text{AR or RW} \tag{8}$$

where $\Delta\hat{p}^{\mathrm{B}}_{s,s+h}$ and $\Delta\hat{p}^{\mathrm{F}}_{s,s+h}$ are the h-period ahead commodity price change forecasts from, respectively, the benchmark models and the 'fundamentals' models (3), (4) and (5). We then report the relative MSE differentials as:

$$RMSE = \frac{\mathrm{MSE_B} - \mathrm{MSE_F}^{adj}}{\mathrm{MSE_B}}, \tag{9}$$

with B = AR or RW. So, a positive (negative) value of (9) equal to x $(-x)$ suggests that the fundamentals-based h-quarter ahead forecast is on average 100 x percent more (less) accurate than the corresponding benchmark forecast.

Given (8) we can formulate a test statistic for $H_0\colon\ \mathrm{MSE_B} - \mathrm{MSE_F} = 0$

$$z^{adj}_{\mathrm{MSE}} = \sqrt{T - t_0 - h}\left(\frac{\mathrm{MSE_B} - \mathrm{MSE_F}^{adj}}{\sqrt{Var(\tilde{u}^{adj}_{t+h})}}\right); \quad \mathrm{B} = \mathrm{AR\ or\ RW} \tag{10}$$

with

$$\tilde{u}^{adj}_{t+h} = u^{adj}_{t+h} - (\mathrm{MSE_B} - \mathrm{MSE_F}^{adj})$$

and

$$u^{adj}_{t+h} = \varepsilon^2_{\mathrm{B},s,s+h} - \left(\varepsilon^2_{\mathrm{F}\,s,s+h} - (\Delta\hat{p}^{\mathrm{B}}_{s,s+h} - \Delta\hat{p}^{\mathrm{F}}_{s,s+h})^2\right); \quad s = t_0, \ldots, T-h.$$

We compute the variance of the $\tilde{u}^{adj}_{t+h}$ terms based on a heteroskedasticity and autocorrelation consistent (HAC) variance estimator, as time-varying variance is a feature of commodity price changes and the overlap in observations at forecast horizons $h > 1$ induces serial correlation in the disturbances of our forecasting models.

More specifically, we employ the parametric HAC variance estimator proposed by Den Haan and Levin [11], which has been shown to have good finite sample properties.[16] Clark and West [9, 10] show that in case of *rolling window*-based parameter updating, as is the case in our specification, (10) will be asymptotically distributed according to a standard normal distribution, i.e., $z^{adj}_{\mathrm{MSE}} \sim N(0,1)$ in (10). In the forecast evaluation, we use (10) to conduct a *one-sided* test for the null hypothesis that fundamentals-based commodity price predictions do not significantly outperform those based on our naive, parsimonious benchmark specifications *vis-à-vis* the alternative hypothesis that (3), (4) or (5) outperform either (1) or (2).

[16] In our case the Den Haan and Levin [11] approach entails fitting an AR model to the $\tilde{u}^{adj}_{t+h}$ terms, with the lag order determined by minimizing BIC, and using this estimated AR model to compute the unconditional variance of the $\tilde{u}^{adj}_{t+h}$ terms.

4 Empirical results

4.1 Data description

There are 10 spot indices in total, taken from four distinct sources. Details about the composition and calculation of the different indices appear in the Data Appendix.

From the Commodity Research Bureau, we use the Reuters/Jefferies-CRB Index (CRB), which dates back the farthest of any cross-commodity index: both the overall index and the industrial metals sub-index start in 1947. However, we only go as far back as 1973, based on the availability of the economic fundamental variables. The next longest series, the S&P/Goldman Sachs Index (SPG), starts in 1970, although once again we use data from 1973 onward. The SPG sub-indices for industrial metals and energy start in 1977 and 1983, respectively. We also evaluate the series used in [8], the IMF Non-fuel Commodity Prices Index (IMF), which starts in 1980, along with the IMF industrial metals sub-index. Finally, the Dow Jones-AIG Commodity Index (DJAIG) is the shortest series we use, beginning in 1991, along with its sub-indices for energy and metals. All commodity price data come directly from the companies who publish them, except for the SPG sub-indices, which come from Bloomberg. As discussed in Section 3.1 we take log first differences of all commodity price indices, a transformation chosen to guarantee covariance stationarity.

The exchange rate data for the CRR model come from Bloomberg. We use monthly averages of daily bilateral dollar exchange rates for the Canadian dollar, the Australian dollar, the New Zealand dollar, the South African rand, and the Chilean peso. Chilean exchange rate data are only used when evaluating our models for the DJ-AIG indices, since these data only extend back as far as 1991.

For the factor-augmented models (4) and (5) we combine the exchange rate data with additional fundamental predictor variables in a panel. These additional variables comprise a set of standard macro-economic time series across major developed and developing countries, such as industrial production, business and consumer confidence data, retail sales volumes, unemployment rates, core consumer prices (excluding food and energy), money aggregates and interest rates (source: OECD). They also include data on inventories and production of industrial metals, oil, natural gas and coal (source: Energy Information Administration), as well as the Baltic Dry Index (BDI). The BDI is an index which captures the costs of ocean shipping, aggregating the prices of many different routes and types of shipping vessels. It is maintained by the Baltic Exchange, a commodity exchange. Our BDI data come from Bloomberg as far back as 1985, and they are averaged over the month from daily data. Before that, going back to 1973, we use monthly data on aggregated ocean shipping rates that we splice onto our BDI data for the pre-1985 period.[17]

The predictor variables are also transformed to guarantee covariance stationarity. In general, this means that the real variables are expressed in log first differences, and the rate variables, such as unemployment and interest rate, are simply expressed in first differences; see the Data Appendix for more details. With respect to prices and monetary aggregates, we transform these series into first differences of annual growth rates to guarantee that the dynamic properties of the transformed series are comparable to those of the rest of the predictor variable panel.[18] Except for the BDI, exchange rate data and interest rates, the remaining series in our predictor variable panels for models (4) and (5) are assumed to be observable with a one-month lag. So, for example, in February 2009 agents only observe industrial production or the consumer price index up to January 2009. Hence, for these (typically macroeconomic) time series we lag the series by one month before including them in our panels, thus reducing the potential bias in favor of our factor-augmented models in the forecast evaluations.

The cross-sectional sizes of the panels used in the factor-augmented models vary across the different commodity price indices we evaluate, as different indices have different time spans that determine the availability of the variables used in the panel. For the CRB aggregate and industrial metals indices, the full sample for both the commodities prices and the predictor variables panel is 1973.03-2009.2 with a total of $N = 96$ series in the panel. For the aggregate SPG commodities price index, the full sample also equals 1973.03-2009.2 with $N = 96$. For the SPG industrial metals sub-index, the full sample equals 1977.02-2009.2 with cross-sectional size of $N = 112$ for the predictor variable panel, whereas for the SPG energy sub-index they are 1983.02-2009.02 and $N = 127$, respectively. For the two IMF commodities price series, the full sample spans the period 1980.02-2009.02, and we use $N = 122$ series in the panels used for our factor-augmented models. Finally, for the three DJAIG series, the data span the period 1991.02-2009.02, and there are $N = 143$ series in the corresponding panels of predictor variables.

4.2 Results

As discussed in Section 3.1, for all ten commodity price indices listed above we assess the forecasting performance of our three fundamentals-based forecast methods (the CRR

[17] We thank Lutz Killian for providing us with this data, which he uses in [27]. For our purposes, we use the nominal raw version of his series, instead of the real detrended version used in his paper.

[18] This particular transformation acknowledges that series like log price levels and log money aggregate levels behave as if they were $I(2)$, possibly because of mean growth shifts due to policy regime changes, financial liberalizations and other phenomena.

exchange rate-based model (3) and our two factor-augmented models (4) and (5)) relative to two simple benchmark forecasts: those based on an autoregressive (AR) specification and those based on the unconditional mean or random walk (RW) model (respectively (1) and (2)). In Tables 1-10 the last columns (denoted FX) report comparisons of the factor-augmented models against the CRR model used as a benchmark, as will be explained below. All forecasting models, including the benchmark models, are updated for each forecast based on a fixed rolling window of data (see Section 3.2), which we set equal to a 10-year period resulting in 120 monthly observations.[19]

The forecasts for our ten commodity price indices apply to five time horizons (in months): $h = 1$, $h = 3$, $h = 6$, $h = 12$ and $h = 24$, as commonly analyzed in the literature. In each re-estimation of our forecasting models, we determine a version of each of our two factor-augmented regressions (4) and (5) based on our modified information criterion in (6). Using this criterion in (6) we simultaneously select the optimal lag order from $j = 0, \ldots, 12$ (where $p = 0$ means no lagged commodity price changes included in the model) as well as the optimal number of factors across $i = 1, \ldots, 6$ such that the value of the criterion is minimized. In case of the AR benchmark (1) as well as the CRR exchange rates-based model (3) we select that lag order from $p = 0, \ldots, 12$ that minimizes the BIC criterion for these two models.

The forecasting results for the CRB commodity price indices are reported in Tables 1 and 2. When we first focus on the performance of the CRR specification (3), it becomes clear that in an out-of-sample context it is not structurally outperforming random walk and autoregressive forecasts: at the shortest horizons its predictions are only significantly better than those based on a random walk, whereas one- and two-years ahead the CRR model can only significantly outperform the AR benchmark.

Factor-augmented models that utilize principal components extracted from the corresponding panel of global economic data perform quite poorly and never really significantly outperform the naive benchmark predictions. However, when PLS regression is used to generate factor-augmented commodity price forecasts, the results are more encouraging. For the overall CRB index (see Table 1), PLS regression-based specifications provide significantly better predictions than both benchmark models at the one-month and one-quarter horizons. In Table 2, we have a similar outcome for the industrial medals CRB sub-index, although PLS-based factor models are also outperforming both benchmarks one-year ahead.

In case of the DJ-AIG commodity price indices in Tables 3-5, there is arguably some value added in using exchange rate-based models when predicting the overall index (Table 3), but a lot less so for the energy and metals sub-indices (Tables 4 and 5). Compared to the

[19] Thus, $\omega = 120$ in the forecast scheme outlined in Section 3.2.

CRB indices factor-augmented models appear to be less useful: only in case of the overall DJ-AIG index PLS-based models are able to significantly outperform both benchmarks at the 3-month and 6-month horizons.

Tables 6-8 reports on the out-of-sample performance for our next group of commodity price indices: the S&P/Goldman-Sachs (SPG) indices. The CRR exchange rates-based model (3) is able to significantly outperform naive benchmark projections only at the two-year horizon. Also, forecasts based on both (4) and (5) cannot be deemed to be structurally more accurate than those based on a random walk or autoregressive specifications, although PC-based regressions are successful at $h = 24$ in case of the SPG-Energy index.

Finally, we discuss the results for the IMF indices, as reported in Tables 9 and 10. The CRR specification is doing well in outperforming both benchmark models at the one-month horizon in case of the aggregate index (Table 10), but not for the industrial metals sub-index. Turning to the factor-augmented approaches we find a rather counter-intuitive result: PLS-based factor model forecasts significantly outperform the benchmark projections 1-month and 3-months ahead for aggregate IMF index, but this result disappears in case of the metals sub-index.

The results above suggest that neither the exchange rate approach (as in the CRR model) nor a broader approach that uses information from larger data sets including both exchange rates and other macrovariables (as in our factor-augmented models) are overwhelmingly successful in predicting commodity price dynamics. Nonetheless, the results in Tables 1-10 show that the CRR and the PLS-based factor models are occasionally able to outperform simple benchmark models in an out-of-sample context. In light of this outcome, one wonders whether the extra information of the PLS-based factor model *vis-à-vis* the CRR model is significant enough to warrant its use. To investigate this we compare the out-of-sample commodity price changes from the CRR framework with the following model:

$$\Delta p_{t+h,t} = \alpha^h + \sum_{m=1}^{M} \gamma_m \Delta e_t^m + \sum_{i=1}^{r} \beta_i^h f_{i,t}^{PLS} + \sum_{j=1}^{k} \rho_i \Delta p_{t-j+1,t-j} + \epsilon_{t+h,t}, \tag{11}$$

where the r PLS factors are now extracted from a panel of predictor variables that *excludes* the M commodity dollar exchange rates, and we again use the BICM criterion (6) to determine r and k. An out-of-sample comparison between model (11) and model (3), therefore, provides insight about how valuable for forecasting purposes is the extra information (on top of the exchange rates) embedded in the large data set. The out-of-sample analysis for (11) is carried out as outlined in Section 3.2, but now with the CRR model (3) as the benchmark.

In the *last* columns of Tables 1-10, denoted *FX*, we report the results of the out-of-sample comparison between (11) and (3). Of these 50 out-of-sample exercises (5 horizons for 10 commodity price indices), the extra information embedded in the predictor variable panels turns out to improve significantly their forecasting performance against the exchange-rate approach in 24 cases, in particular for the CRB and DJ-AIG indices. And in the majority of those 24 cases, both the CRR model and the *original* PLS-based factor model significantly outperform at least one of the two simple, naive, benchmark models. Hence, the case can be made that the PLS-based factor model has a slight edge over the CRR model in modeling commodity price dynamics.

A potential reason why both the CRR and the factor-augmented models cannot structurally outperform naive benchmark forecast might well be due to the fact that market-specific information is the dominant driver of commodity price dynamics. This market-specific information, such as speculative strategies, should, however, be present in futures and forwards contracts that price in expectations for commodity prices in the near future. We therefore collected a number of time series on 1-, 3-, 6- and 12-months ahead futures and forward rates for prices of food commodities, oil, precious metals and industrial metals; see the Data Appendix for more details. Next, we took appropriate transformations of these futures and forward rates (to make them covariance stationary), added them to our panels of predictor variables, and evaluated whether the addition of such market-specific information enables the factor-augmented models to structurally outperform the naive benchmark predictions. Regrettably, however, consistent time series on a broad set of commodity futures and forward rates are only available from the mid-1980s onwards. Thus, a proper comparison with the factor-augmented results in Tables 1-10 is not feasible for all 10 commodity price indices. We therefore limit the above mentioned experiment to the DJ-AIG price indices, and the corresponding results can be found in Tables 11-13.

If one compares the results in Tables 11-13 with the results of the factor-augmented model in Tables 3-5, which exclude information embedded in commodities futures/forwards rates, it becomes quite clear that the forecasting performances are substantially unchanged across data sets. Thus, qualitatively, the factor-augmented model results in Tables 11-13 relative to the naive benchmark models remain as weak as was originally the case in Tables 3-5.

5 Conclusion

Can we obtain forecasts of commodity price movements that systematically improve upon naive statistical benchmarks? The basic message of the paper is one of inconclusiveness. While our results corroborate the notion that commodity currencies are somewhat privileged variables in terms of their predictive power, we are unable to obtain robust validation of this notion across commodity indices and across forecasting horizons. Information from larger sets of macrovariables can help improve our predictions, but their forecasting properties are nuanced and by no means overwhelming.

To make a point of some potential relevance for the current (late 2009) policy debate in light of our results, stronger exchange rates in commodity-exporter countries, improved confidence and business conditions in China and other Asian NICS, as well as the positive drift of the BDI, all point to buoyant conditions in commodity markets going forward. The risks of a recrudescence in global headline inflation are skewed on the upside. But acknowledging these risks is not tantamount to fostering concerns about policymakers' ability to guarantee price stability, thus advocating a fast withdrawal of accommodation worldwide. Analyses like ours suggest that forecasts of commodity prices provide at their very best only highly noisy information about their actual future trajectories and persistence. All the more so, estimates of the inflationary pressures associated with expected commodity price swings remain tentative at best. Excessive confidence in the forecast of a forthcoming commodity price surge, or even increased dispersion in global policymakers' views and beliefs about future inflation risks, can become the catalyzer of (or the pretext for) a premature tightening of the global policy mix even though the international outlook remains vulnerable to negative shocks, with potentially devastating consequences for the real economy worldwide.

Concluding as we started with a quote by Bernanke [3], there is a key open question for a research agenda focused on understanding and predicting swings in commodity prices: "What are the implications for the conduct of monetary policy of the high degree of uncertainty that attends forecasts of commodity prices? Although theoretical analyses often focus on the case in which policymakers care only about expected economic outcomes and not the uncertainty surrounding those outcomes, in practice policymakers are concerned about the risks to their projections as well as the projections themselves. How should those concerns affect the setting of policy in this context?" It is our (strong) prediction that future research will very much take these questions to heart.

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Table 1: Forecast evaluation for the aggregate CRB commodity price index; 1973.03 - 2009.02

	CRR		PC Regression		PLS Regression		
h	RW	AR	RW	AR	RW	AR	FX
1	0.07	-0.01	0.00	-0.01	0.20	0.14	0.18
	(1.34)**	(-0.56)	(0.03)	(-0.63)	(1.86)**	(0.99)*	(1.44)**
3	0.02	0.02	-0.02	0.00	0.14	0.14	0.25
	(0.34)	(0.59)	(-0.88)	(-0.16)	(1.26)**	(0.82)*	(1.95)***
6	0.02	0.05	-0.06	-0.02	-0.10	-0.09	-0.05
	(0.25)	(1.14)*	(-0.71)	(-0.55)	(-0.56)	(-0.73)	(-0.41)
12	0.02	0.06	-0.09	-0.02	0.00	0.02	0.14
	(0.25)	(0.93)*	(-0.85)	(-0.24)	(0.00)	(0.16)	(1.43)**
24	-0.01	0.07	-0.19	-0.05	-0.59	-0.48	-0.09
	(-0.08)	(1.56)**	(-1.97)	(-0.57)	(-2.84)	(-2.40)	(-0.37)

Notes: The table reports the relative improvement in the MSE for either the CRR exchange rate-based model (3), versions of the principal components-based factor-augmented model (4) or versions of the PLS regression-based factor-augmented model (5) relative to either the AR model (1) or the random walk-based model (2). This relative MSE improvement is defined in (9). In parentheses we report the test statistic (10) for the null hypothesis that the corresponding MSE differential is zero, whereas a * (**) [***] denotes a rejection of this null hypothesis in favor of the alternative hypothesis that the MSE differential is positive at a 10% (5%) [1%] significance level. Under the heading 'CRR' we report the results for model (3) relative to the AR benchmark (column 'AR') and the random walk-based benchmark (column 'RW'), under the heading 'PC' we report these for the principal components-based model (4) with factor- and lag order selection based on the BICM criterion as in (6), and under the heading 'PLS' we report the results for the PLS regression-based model (5) with factor- and lag order selection also based on the BICM criterion as in (6). Finally, in case of PLS regression the column dented by 'FX' reports forecast results of (11), using PLS factors extracted from a predictor variable panel *without* exchange rates, relative to (3) as a benchmark.

Table 2: Forecast evaluation for the CRB Industrial Metals sub-index; 1973.03 - 2009.02

	CRR		PC Regression		PLS Regression		
h	RW	AR	RW	AR	RW	AR	FX
1	0.12	0.01	0.11	0.03	0.20	0.09	0.10
	(2.30)***	(0.43)	(2.71)***	(1.37)**	(3.88)***	(1.10)*	(1.26)**
3	0.06	0.00	0.00	0.00	0.14	0.10	0.18
	(1.23)**	(0.04)	(0.11)	(-0.11)	(0.90)*	(0.72)	(1.33)**
6	0.03	0.02	-0.01	0.02	-0.01	0.01	0.03
	(0.70)	(0.70)	(-0.19)	(0.26)	(-0.04)	(0.10)	(0.27)
12	0.02	0.04	-0.09	0.00	0.13	0.17	0.23
	(0.22)	(0.73)	(-1.01)	(0.04)	(0.92)*	(1.26)**	(2.12)***
24	0.00	0.08	-0.13	0.01	-0.37	-0.30	0.08
	(-0.04)	(1.80)**	(-1.42)	(0.07)	(-1.92)	(-1.64)	(0.23)

Notes: See the notes for Table 1.

Table 3: Forecast evaluation for the aggregate DJ-AIG commodities price index; 1991.02 - 2009.02

	CRR		PC Regression		PLS Regression		
h	RW	AR	RW	AR	RW	AR	FX
1	0.24	0.09	0.19	0.03	0.40	0.18	0.19
	(2.96)***	(1.59)**	(0.58)	(0.95)*	(0.60)	(1.03)*	(1.48)**
3	0.05	0.05	0.00	0.03	0.48	0.48	0.43
	(1.16)*	(0.98)*	(0.05)	(1.06)*	(0.94)*	(0.93)*	(0.98)*
6	0.00	0.01	-0.08	0.03	0.06	0.17	0.18
	(0.00)	(0.50)	(-0.22)	(0.55)	(1.31)**	(0.80)	(3.85)***
12	0.18	0.09	0.25	0.34	0.20	0.33	0.39
	(0.83)*	(1.93)***	(0.84)*	(1.33)**	(0.62)	(0.86)*	(1.26)**
24	0.17	0.13	0.62	0.82	0.04	0.08	0.17
	(0.71)	(1.62)**	(2.14)***	(1.80)**	(0.07)	(0.19)	(0.57)

Notes: See the notes for Table 1.

Table 4: Forecast evaluation for the DJ-AIG Energy sub-index; 1991.02 - 2009.02

	CRR		PC Regression		PLS Regression		
h	RW	AR	RW	AR	RW	AR	FX
1	0.17	-0.05	0.24	0.01	0.29	0.06	0.16
	(1.44)**	(-1.23)	(0.13)	(0.32)	(0.51)	(0.30)	(0.33)
3	-0.03	-0.05	-0.03	-0.04	0.35	0.37	0.40
	(-0.52)	(-1.24)	(-0.62)	(-0.88)	(0.72)	(0.83)*	(0.96)*
6	-0.08	-0.04	-0.09	-0.03	0.10	0.22	0.28
	(-0.69)	(-2.89)	(-0.62)	(-1.43)	(0.28)	(0.48)	(0.55)
12	0.07	0.00	-0.12	0.02	-0.03	0.22	0.32
	(0.32)	(0.11)	(-0.49)	(0.10)	(-0.07)	(0.49)	(0.79)
24	0.12	0.12	0.37	0.51	0.02	0.48	0.52
	(0.05)	(2.05)***	(1.01)*	(1.11)*	(0.04)	(0.56)	(0.93)*

Notes: See the notes for Table 1.

Table 5: Forecast evaluation for the DJAIG Industrial Metals sub-index; 1991.02 - 2009.02

	CRR		PC Regression		PLS Regression		
h	RW	AR	RW	AR	RW	AR	FX
1	0.30	0.04	0.23	-0.02	0.21	-0.12	-0.05
	(1.43)**	(1.16)*	(0.32)	(-0.54)	(1.15)*	(-0.68)	(-0.31)
3	0.10	-0.03	0.04	0.00	0.18	0.08	0.13
	(1.09)*	(-0.50)	(0.64)	(0.02)	(0.77)	(0.36)	(0.87)*
6	0.01	0.00	0.02	0.07	0.03	0.10	0.13
	(0.10)	(-0.39)	(0.04)	(0.69)	(0.07)	(0.71)	(1.16)*
12	-0.08	-0.04	0.22	0.32	0.20	0.26	0.33
	(-0.36)	(-0.73)	(1.36)**	(1.53)**	(0.12)	(1.92)***	(2.42)***
24	-0.24	0.00	-0.19	0.02	-0.13	0.06	0.11
	(-1.35)	(-0.13)	(-1.26)	(0.27)	(-0.34)	(0.66)	(0.64)

Notes: See the notes for Table 1.

Table 6: Forecast evaluation for the aggregate SPG commodities price index; 1973.03 - 2009.02

	CRR		PC Regression		PLS Regression		
h	RW	AR	RW	AR	RW	AR	FX
1	0.15	-0.02	0.16	-0.02	0.10	-0.06	-0.02
	(1.80)**	(-1.02)	(0.89)*	(-1.16)	(0.69)	(-0.71)	(-0.20)
3	-0.06	-0.01	0.00	0.04	-0.03	0.04	0.11
	(-1.65)	(-0.54)	(-0.13)	(1.86)**	(-0.27)	(0.30)	(0.71)
6	-0.03	-0.01	-0.04	0.01	-0.04	0.02	0.08
	(-0.23)	(-0.30)	(-0.01)	(0.87)*	(-0.49)	(0.23)	(1.15)*
12	0.10	0.04	0.03	0.01	-0.07	-0.07	0.06
	(0.69)	(1.13)*	(0.14)	(0.22)	(-0.59)	(-0.45)	(0.35)
24	0.13	0.14	-0.07	-0.02	-0.49	-0.39	-0.07
	(1.16)*	(1.55)**	(-0.73)	(-0.23)	(-0.89)	(-2.04)	(-0.31)

Notes: See the notes for Table 1.

Table 7: Forecast evaluation for the SPG Energy sub-index; 1983.02 - 2009.02

	CRR		PC Regression		PLS Regression		
h	RW	AR	RW	AR	RW	AR	FX
1	0.14 (1.46)**	-0.04 (-1.56)	0.15 (1.51)**	-0.01 (-0.63)	0.35 (1.59)**	0.18 (1.15)*	0.23 (1.54)**
3	-0.06 (-0.67)	-0.02 (-0.90)	-0.02 (-0.19)	0.01 (0.52)	0.13 (0.71)	0.21 (0.92)*	0.25 (1.08)*
6	-0.05 (-0.46)	0.00 (0.10)	-0.10 (-0.35)	-0.03 (-0.84)	-0.01 (-0.09)	0.02 (0.18)	0.06 (0.54)
12	0.10 (0.32)	0.02 (0.71)	-0.08 (-0.94)	-0.09 (-1.92)	-0.05 (-0.19)	-0.09 (-0.27)	-0.03 (-0.11)
24	0.18 (1.59)**	0.04 (0.77)	0.27 (2.09)***	0.16 (1.21)*	0.40 (0.65)	0.23 (0.45)	0.31 (0.43)

Notes: See the notes for Table 1.

Table 8: Forecast evaluation for the SPG Industrial Metals sub-index; 1977.02 - 2009.02

	CRR		PC Regression		PLS Regression		
h	RW	AR	RW	AR	RW	AR	FX
1	0.13 (1.61)**	-0.02 (-1.16)	0.17 (0.28)	0.02 (0.97)*	0.16 (1.22)*	0.01 (0.08)	0.02 (0.15)
3	-0.03 (-0.59)	-0.07 (-1.97)	0.07 (1.65)**	0.06 (1.95)***	0.11 (0.74)	0.06 (0.47)	0.13 (1.13)*
6	-0.03 (-0.25)	-0.04 (-1.36)	0.01 (0.11)	0.02 (0.62)	-0.08 (-0.24)	-0.12 (-0.45)	-0.05 (-0.26)
12	-0.02 (-0.16)	0.01 (0.16)	-0.03 (-0.28)	0.02 (0.22)	-0.05 (-0.19)	-0.10 (-0.67)	-0.04 (-0.25)
24	-0.12 (-0.49)	-0.01 (-0.63)	-0.38 (-2.01)	-0.25 (-1.58)	-0.19 (-1.29)	-0.12 (-0.88)	-0.09 (-0.51)

Notes: See the notes for Table 1.

Table 9: Forecast evaluation for the aggregate, non-fuel IMF commodities price index; 1980.02 - 2009.02

	CRR		PC Regression		PLS Regression		
h	RW	AR	RW	AR	RW	AR	FX
1	0.34 (1.49)**	0.03 (1.49)**	0.32 (1.20)*	-0.01 (-0.69)	0.44 (2.33)***	0.18 (1.37)**	0.17 (1.48)**
3	0.15 (3.31)***	-0.01 (-0.29)	0.13 (1.86)**	-0.01 (-0.37)	0.25 (2.15)***	0.10 (1.00)*	0.14 (1.31)**
6	0.01 (0.36)	0.01 (0.37)	0.00 (-0.01)	0.03 (0.98)*	-0.10 (-0.37)	-0.10 (-0.46)	-0.06 (-0.24)
12	0.03 (0.40)	0.04 (0.93)*	-0.07 (-0.75)	-0.02 (-0.06)	0.15 (0.18)	0.14 (0.41)	0.23 (0.83)*
24	-0.08 (-1.03)	0.00 (-0.03)	-0.39 (-2.31)	-0.29 (-2.20)	-0.14 (-0.91)	-0.07 (-0.49)	-0.03 (-0.26)

Notes: See the notes for Table 1.

Table 10: Forecast evaluation for the IMF Industrial Metals sub-index; 1980.02 - 2009.02

	CRR		PC Regression		PLS Regression		
h	RW	AR	RW	AR	RW	AR	FX
1	0.15 (1.80)**	0.01 (0.25)	0.14 (1.35)**	0.02 (0.46)	0.10 (0.85)*	-0.04 (-0.32)	0.01 (0.04)
3	0.02 (0.34)	-0.05 (-0.80)	0.05 (0.71)	0.02 (0.39)	0.14 (0.90)*	0.06 (0.50)	0.12 (1.38)**
6	0.01 (0.05)	-0.02 (-0.50)	0.05 (0.18)	0.07 (0.84)*	0.10 (0.24)	0.08 (0.31)	0.12 (0.59)
12	0.05 (0.41)	0.03 (0.92)*	-0.01 (-0.06)	0.02 (0.14)	0.23 (0.30)	0.19 (0.63)	0.25 (0.90)*
24	-0.08 (-0.52)	0.01 (0.47)	-0.38 (-1.78)	-0.30 (-1.83)	-0.09 (-0.32)	-0.08 (-0.37)	-0.05 (-0.24)

Notes: See the notes for Table 1.

Table 11: Forecast evaluation for the aggregate DJ-AIG commodities price index with futures included in the underlying panel; 1991.02 - 2009.02

	PC Regression		PLS Regression	
h	RW	AR	RW	AR
1	0.26	0.09	0.58	0.32
	(0.33)	(0.87)*	(1.23)*	(0.46)
3	0.10	0.11	0.45	0.45
	(0.68)	(1.15)*	(0.95)*	(0.98)*
6	0.03	0.05	0.07	0.17
	(0.27)	(2.17)***	(1.04)*	(0.75)
12	0.10	-0.02	0.22	0.32
	(0.25)	(-0.18)	(0.58)	(0.36)
24	0.00	-0.04	0.09	0.12
	(-0.02)	(-0.19)	(0.15)	(0.35)

Notes: See the notes for Table 1.

Table 12: Forecast evaluation for the aggregate DJ-AIG Energy sub-index with futures included in the underlying panel; 1991.02 - 2009.02

	PC Regression		PLS Regression	
h	RW	AR	RW	AR
1	0.25	0.03	0.32	0.07
	(0.73)	(0.58)	(0.37)	(0.27)
3	0.04	0.02	0.39	0.40
	(0.37)	(0.59)	(0.66)	(0.78)
6	-0.07	-0.03	0.13	0.24
	(-0.25)	(-0.56)	(0.27)	(0.76)
12	-0.30	-0.40	0.02	0.19
	(-0.47)	(-0.97)	(0.04)	(0.26)
24	-0.03	0.10	0.02	0.41
	(-0.09)	(0.34)	(0.03)	(0.83)*

Notes: See the notes for Table 1.

Table 13: Forecast evaluation for the aggregate DJ-AIG Industrial Metals sub-index with futures included in the underlying panel; 1991.02 - 2009.02

	PC Regression		PLS Regression	
h	RW	AR	RW	AR
1	0.35	0.08	0.41	0.07
	(0.30)	(1.08)*	(1.29)**	(0.54)
3	0.16	0.09	0.17	0.08
	(0.70)	(1.59)**	(0.73)	(0.42)
6	0.07	0.08	-0.03	0.03
	(0.28)	(1.06)*	(-0.04)	(0.12)
12	0.06	0.10	0.15	0.24
	(0.23)	(0.30)	(0.13)	(1.78)**
24	-0.20	0.04	-0.09	0.11
	(-0.90)	(0.37)	(-0.25)	(1.54)**

Notes: See the notes for Table 1.

Data Appendix

Data Codes

Code	Country	Code	Transformation X_t of raw series Y_t
a	Canada	1	$X_t = ln(Y_t) - ln(Y_{t-1})$
b	France	2	$X_t = Y_t - Y_{t-1}$
c	Germany	3	$X_t = ln(Y_t/Y_{t-12}) - ln(Y_{t-1}/Y_{t-13})$
d	Italy	4	$X_t = ln(\sum_{k=0}^{11} Y_{t-k}/12) - ln(\sum_{k=1}^{12} Y_{t-k}/12)$
e	Japan	5	$X_t = Y_t$
f	United Kingdom		
g	United States		
h	Brazil	Code	Commodity price series
i	India	v	CRB, CRB ind. metal, SPG
j	Indonesia	w	DJAIG, DJAIG energy, DJAIG ind. metal
k	South Africa	x	IMF, IMD ind. metal
l	OECD	y	SPG energy
m	G7	z	SPG ind. metal

Data Description

Variable	Countries	Source	Transform	Indices
Australian Dollar Exchange Rate	-	Bloomberg	1	vwxyz
Canadian Dollar Exchange Rate	-	Bloomberg	1	vwxyz
New Zealand Dollar Exchange Rate	-	Bloomberg	1	vwxyz
South African Rand Exchange Rate	-	Bloomberg	1	vwxyz
Chilean Peso Exchange Rate	-	Bloomberg	1	w
Baltic Dry Index (BDI)	-	Bloomberg	1	vwxyz
Industrial Production	abcdefg	OECD	1	vwxyz
Industrial Production	j	OECD	1	w
Nominal Short Term Interest Rates (3 Month)	abceg	OECD	2	vwxyz
Nominal Short Term Interest Rates (3 Month)	df	OECD	2	wxyz
Real Short Term Interest Rates (3 Month)	abceg	OECD	2	vwxyz
Real Short Term Interest Rates (3 Month)	df	OECD	2	wxyz
Long Term Interest Rates (10 Year)	abcfgk	OECD	2	vwxyz
Long Term Interest Rates (10 Year)	e	OECD	2	w
Business Confidence Indicator	g	OECD	5	vwxyz
Business Confidence Indicator	e	OECD	5	wxyz
Business Confidence Indicator	bcdeflm	OECD	5	w
Consumer Confidence Indicator	bcdf	OECD	5	wxyz
Consumer Confidence Indicator	fl	OECD	5	wxy
Consumer Confidence Indicator	a	OECD	5	w
Unemployment	aefg	OECD	2	vwxyz
Unemployment	b	OECD	2	wxy
Unemployment	h	OECD	2	wy
Retail Trade Volume	acefg	OECD	1	vwxyz
Retail Trade Volume	b	OECD	1	wxyz
Retail Trade Volume	k	OECD	1	wxy
Retail Trade Volume	d	OECD	1	w
Hourly Earnings in Manufacturing	dfg	OECD	1	vwxyz
Hourly Earnings in Manufacturing	e	OECD	4	vwxyz
Hourly Earnings in Manufacturing	a	OECD	1	vxyz
Goods Exports	abcgefghk	OECD	1	vwxyz
Goods Exports	ij	OECD	1	w
Goods Imports	abcgefghk	OECD	1	vwxyz
Goods Imports	ij	OECD	1	w

Term Slope Structure (Long term - short term rates)	abcg	OECD	5	vwxyz
Term Slope Structure (Long term - short term rates)	f	OECD	5	wxy
Term Slope Structure (Long term - short term rates)	e	OECD	5	w
Core CPI	abcdefgl	OECD	3	vwxyz
Core CPI	m	OECD	3	vz
Broad Money (M3)	agk	OECD	3	vwxyz
Broad Money (M3)	i	OECD	3	wxyz
Broad Money (M3)	el	OECD	3	wy
Broad Money (M3)	f	OECD	3	w
Narrow money (M1)	aegl	OECD	3	vwxyz
Narrow money (M1)	ik	OECD	3	wxyz
Narrow money (M1)	f	OECD	3	w
LME Copper Warehouse Stocks	-	EIA	1	vwxyz
LME Lead Warehouse Stocks	-	EIA	1	vwxyz
LME Zinc Warehouse Stocks	-	EIA	1	vwxyz
LME Aluminum Warehouse Stocks	-	EIA	1	wxy
LME Nickel Warehouse Stocks	-	EIA	1	wxy
LME Tin Warehouse Stocks	-	EIA	1	w
Crude Oil Stocks, Non-SPR (Strategic Petrol Reserve)	-	EIA	1	vwxyz
Crude Oil Stocks, Total	-	EIA	1	vwxyz
Crude Oil Stocks, SPR	-	EIA	1	wxy
Jet Fuel Stocks	-	EIA	1	vwxyz
Motor Gasoline Stocks	-	EIA	1	vwxyz
Residual Fuel Oil Stocks	-	EIA	1	vwxyz
Other Petroleum Products Stocks	-	EIA	1	vwxyz
Total Petroleum Stocks	-	EIA	1	vwxyz
United States Crude Oil Production	-	EIA	1	vwxyz
Non-OPEC Crude Oil Production	-	EIA	1	vwxyz
World Crude Oil Production	-	EIA	1	vwxyz
OPEC Crude Oil Production	-	EIA	1	vwxyz
Total World Coal Stocks	-	EIA	1	vwxyz
Distillate Fuel Oil Stocks	-	EIA	1	wxyz
Propane/Propylene Stocks	-	EIA	1	wxyz
Liquefied Petroleum Gases Stocks	-	EIA	1	wxyz
Natural Gas in Underground Storage - Working Gas	-	EIA	1	wyz
Natural Gas in Underground Storage - Total	-	EIA	1	wyz
Currency: Banknotes and Coin	f	Bank of England	1	vwxyz
Wheat Futures Price (1, 3, and 6 month)	-	Bloomberg	1	w*
Corn Futures Price (1 and 3 month)	-	Bloomberg	1	w*
Hogs Futures Price (1, 3, and 6 month)	-	Bloomberg	1	w*
WTI Futures Price (1, 3, 6, and 12 month)	-	Bloomberg	1	w*
Heating Oil Futures Price (1, 3, 6, and 12 month)	-	Bloomberg	1	w*
Brent Crude Futures Price (3 and 6 month)	-	Bloomberg	1	w*
Copper Futures Price (3 and 6 month)	-	Bloomberg	1	w*
Gold Futures Price (3, 6, and 12 month)	-	Bloomberg	1	w*
Silver Futures Price (3, 6, and 12 month)	-	Bloomberg	1	w*
Lead Forward Price (3 and 15 month)	-	Bloomberg	1	w*
Copper Forward Price (3 month)	-	Bloomberg	1	w*
Nickel Forward Price (3 month)	-	Bloomberg	1	w*
Tin Forward Price (3 month)	-	Bloomberg	1	w*
Zinc Forward Price (3 month)	-	Bloomberg	1	w*
Aluminum Forward Price (3 month)	-	Bloomberg	1	w*
Dependent Variables				
Reuters/Jefferies Commodity Price Index	-	CRB	1	v
CRB Industrial Metals Price Index	-	CRB	1	v
S&P/Goldman Sachs Commodity Price Index	-	Goldman Sachs	1	v
Dow Jones/AIG Commodity Price Index	-	Dow Jones	1	w
DJAIG Energy Commodity Price Index	-	Dow Jones	1	w
DJAIG Industrial Metals Price Index	-	Dow Jones	1	w
IMF Global Commodity Price Index	-	IMF	1	x
IMF Industrial Metals Price Index	-	IMF	1	x
S&P/Goldman Sachs Energy Commodities Price Index	-	Goldman Sachs	1	y
S&P/Goldman Sachs Industrial Metals Price Index	-	Goldman Sachs	1	z

*These are only used in the DJAIG models for Tables 11-12.