Common Factors of Commodity Prices*

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Abstract

In this paper we extract latent factors from a large cross-section of commodity prices, including fuel and non-fuel commodities. We decompose each commodity price series into a global (or common) component, block-specific components and a purely idiosyncratic shock. We find that the bulk of the fluctuations in commodity prices is well summarized by a single global factor. This global factor is closely related to fluctuations in global economic activity and its importance in explaining variations in commodity prices has increased since the beginning of the 2000s, especially for oil.

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1 Introduction

Primary commodities, in the form of raw or partially processed goods, have been traditionally case examples of traded goods across borders and account for a significant share of international trade. Despite the secular decline in commodity-intensive sectors in advanced economies, primary commodities continue to have a central role in transportation, manufacturing processes, and in the food supply. The fast economic expansion of China and a number of other emerging market economies has also contributed to a rapid increase in the demand for industrial commodities since the beginning of the new millennium.

Most primary commodities are bought and sold around the globe in well-organized markets where physical and derivative trading take place. Like stock exchanges, commodity exchanges feature institutional and regulatory frameworks that ensure valuable protection to commodities traders and a high level of market liquidity. This is reflected by the fact that purely financial transactions currently outpace transactions in which physical delivery actually occurs.

As far as financial asset returns are concerned, it has been long recognized that they are characterized by a high degree of co-movement (see, for a recent survey, Connor and Korajczyk, 2010). This feature is at the heart of the asset pricing theory and implies that a few underlying factors explain the bulk of the fluctuations in asset returns. Recently, Miranda-Agrippino and Rey (2015) also find evidence of international co-movement in the returns of a large panel of risky assets. A few research studies, as well as more informal narratives, indicate that international commodity prices also exhibit commonalities. The presence of strong co-movement among prices of a broad range of seemingly unrelated commodities might seem puzzling, given that there are many specific factors affecting supply and demand in each market. Pindyck and Rotemberg (1990) described the phenomenon as "excess co-movement" among commodity prices.

In this paper, we analyst the degree of co-movement in international commodity returns by studying a broad range of commodities that are representative of the global market. To do so, we estimate a dynamic factor model with a block structure to decompose each commodity price series into a global (or common) component, block-specific components related to specific commodity markets and a purely idiosyncratic shock. The distinction between global, local and idiosyncratic components allows for the presence of shocks of different nature, having distinct consequences on the cross-correlation between commodity prices.

We find that there is a single global factor driving the bulk of commodity price fluctuations. The global factor is persistent and follows the major expansion and contraction phases in the international business cycle with the largest declines following recession periods. It is also strongly related to measures of economic activity, which suggests a close link to demand determinants. This is further corroborated by the fact that the global factor has homogenous effects on all markets and hence limited effects on relative prices. Since the start of the new millennium, the relevance of the global factor has increased, especially for oil.

We compute model-based historical decompositions of commodity price changes and we find that the global factor accounts for a larger fraction of commodity price fluctuations in episodes typically associated with changes in global economic activity, such as the world economic expansion that started around 2003 and the steep contraction during the Great Recession. By contrast, block components explain most of the fluctuations in commodity prices during episodes conventionally associated with supply or other commodity-specific shocks. For oil prices, we found that fuel-specific factors are the main underlying sources of oil price changes that occurred before the 2000s, such as the collapse of OPEC in 1986 and the Persian Gulf War of 1990-1991. The structural analysis in Kilian and Murphy (2014) and Kilian and Lee (2014) support this result, showing that oil-specific demand shocks and exogenous shifts in supply were a more important determinant of the price of oil before the 2000s.

In order to verify the robustness of the modeling strategy, we perform an out-of-sample validation of the model. Overall, we found that our factor model performs well in forecasting commodity prices and aggregate indices of commodities at short horizons. In particular, the predictive performance of the global factor is higher for the group of commodities for which the historical variance explained by the global factor is larger, such as food and metals. These results are in line with studies of the oil market which have also found evidence that proxies of global demand have predictive power for oil prices (see, Baumeister and Kilian, 2012). Similarly, changes in commodity price indices, in particular industrial raw materials, have been proved to improve the forecast of the price of oil, as these indices are more likely to capture shifts in the global demand for industrial commodities (see, Alquist, Kilian and Vigfusson, 2013). In this respect, our factor-based forecast is a refinement of these earlier approaches. The out-of-sample exercise also shows that for some commodities, notably crude oil, the predictive content of the global factor increased during the Great Recession.

Our paper is not the first to study the co-movement in commodity prices (see, e.g. Alquist and Coibion, 2014; Byrne et al., 2011; West and Wong, 2014; Chen et al., 2014). These other works differ from ours, however, in two ways. First, these papers studied commodity prices in levels instead of returns, focusing on the co-movement at low frequencies. Second, they did not analyze simultaneously all commodity markets and looked at only selected groups of commodities.

The importance of global demand has been extensively documented in the context of the oil market (see, e.g. Barsky and Kilian, 2002; Kilian, 2009; Peersman and Van Robays, 2009; Bodenstein, Guerrieri and Kilian, 2012; Lippi and Nobili, 2012; Aastveit, Bjorland and Thorsrud, 2015). Our paper shows that the association with global economic activity is even stronger when looking at the common factors underlying all the commodities.

The rest of the paper proceeds as follows. Section 2 presents the empirical analysis, the global factor and studies the sources of commodity price fluctuations. Section 3 looks at the predictability and the local forecasting performance of the model. Section 4 concludes.

2 Empirical analysis

2.1 Data

Our dataset consists of the spot prices of 52 internationally traded commodities from different categories: food, beverages, agricultural raw materials, metals and fuel commodities. The source of our data is the International Monetary Fund (IMF) primary commodity price database. We use log changes of monthly averages of daily prices for a sample from January 1980 to December 2015.[1] The composition of the IMF dataset has been designed to represent the world economy, hence it includes the most relevant commodities in terms of trade values. Details are reported in appendix. Table 1 summarizes the structure of the database, and reports for each category the respective weights, which are the commodity trade values as a proportion of the world trade in primary commodities as reported in the UN Comtrade database. Commodities consist of two main blocks: 45 non-fuel commodities and 7 fuel commodities, covering 36.9% and 63.1% of the world trade in commodities. The non-fuel block includes 28 food and beverages commodities and 17 industrial inputs, whose shares in the world trade in commodities are 18.5% and 18.4%, respectively. The fuel block includes 3 different types of crude oil, which account for more than 50% of the world trade in commodities and 4 other less important fuel commodities. The IMF also constructs 10 price indices as weighted averages of individual commodity prices: one overall index which includes the entire set of commodities, and several sub-indices covering the categories described above.

2.2 Model and estimation

The model used here is an approximate dynamic factor model for large cross-sections. This model provides a parsimonious representation of the dynamic co-variation among a set of random variables. Consider an n-dimensional vector of commodity returns $x_t = (x_{1t}, ..., x_{nt})'$. Under the assumption that x_t has a factor representation, each series x_{it} is the sum of the common component - capturing the bulk of cross-sectional co-movements - and an idiosyncratic component reflecting specific shocks or measurement errors:

$$x_{it} = \mu_i + \lambda_{i,1} f_{1,t} + ... + \lambda_{i,r} f_{r,t} + e_{it} \tag{1}$$

where $f_{1,t}, ..., f_{r,t}$ are common pervasive factors affecting all commodities; $\lambda_{i,1}, ..., \lambda_{i,r}$ are the factor loadings measuring the effect of each common factors to commodity i; if λ_i is

[1] A few series start only in the 1990s. Maximum likelihood estimates can be adopted to deal with missing data (see, Banbura and Modugno, 2014).

similar across commodities, then f_t has a limited impact on relative prices. The residual e_{it} is the idiosyncratic component which is assumed to be weakly correlated across commodities and uncorrelated with the common factors. We model the common factors as following an autoregressive process of finite order:

$$A(L)\, f_t = u_t \tag{2}$$

where $f_t = (f_{1,t}, ..., f_{r,t})^{'}$, $A(L) = I - A_1 L - \ldots A_p L^p$ is an $(r \times r)$ filter of finite length p with roots outside the unit circle, and u_t is Gaussian white noise: $u_t \sim i.i.d\mathcal{N}(0, I_r)$.

The idiosyncratic errors are modeled with a block factor structure aiming at capturing in a parsimonious way the correlation withing groups of similar commodities. Specifically, the error e_{it} is decomposed into a component driven by factors that are specific to groups or blocks of commodities and a purely idiosyncratic component:

$$e_{it} = \sum_{j=1}^{K} \gamma_{ij} g_{jt} + v_{it} \tag{3}$$

$$\gamma_{ij} \begin{cases} \neq 0 & \text{if } i \in j \\ = 0 & \text{otherwise} \end{cases}$$

where g_{jt} is an r_b-dimensional vector of block factors; γ_{ij} are block factor loadings and v_{it} is the purely idiosyncratic disturbance. The block factors g_{jt} and the purely idiosyncratic component v_{it} are assumed to follow an autoregressive process of finite order:

$$g_{jt} = \phi_j g_{jt-1} + w_{jt} \tag{4}$$

$$v_{it} = \rho_i v_{it-1} + \varepsilon_{it} \tag{5}$$

with $w_{jt} \sim i.i.d\mathcal{N}(0,1)$ and $\varepsilon_{it} \sim i.i.d\mathcal{N}\left(0, \sigma_i^2\right)$.

We have assumed that the block factors are uncorrelated. This implies that while commodities in the same market can be correlated because of complementarities or common technology shocks, commodity-specific shocks cannot spill over to other commodity markets. This is a strong assumption, which we make in order to maintain the model parsimonious and insure identification. However, estimates are robust to the possibility that market-specific shocks might spill over, provided that the transmission is limited and does not have pervasive effects (see Doz et al., 2012). This assumption is supported by Baumeister and Kilian (2014) who found evidence of negligible spill over effects from oil price shocks to non-fuel commodity

prices. The estimates have also been shown to be robust to non-gaussianity. In this respect, the estimator is a quasi-maximum likelihood estimator in the sense of White (1982).
Principal components are obtained as a special case of our estimates, under the following assumptions:

$$\begin{cases} \gamma_{ij} = 0, \forall i, j \\ \rho_i = 0, \forall i \\ \sigma_i^2 = \bar{\sigma}, \forall i \end{cases}$$

The presence of complementarities between commodities in the same category indicate the possibility of significant local correlations. The unbalanced structure of the dataset as described in the previous section and the presence of strong correlation within categories are two important aspects for the estimation of the common factors. Simple methods, such as principal components, tend to give more weight to categories in the panel that are over-represented. Under these conditions, factors can be poorly estimated (Boivin and Ng, 2006) and the number of factors can be mis-specified (Luciani, 2014). To mitigate this problem and minimize the correlation between idiosyncratic components, one might consider to carefully select commodities before estimation (Alquist and Coibion, 2015). Alternatively, as done in this paper, one can explicitly model the local correlation in specifying the factor model.

Maximum likelihood estimation is implemented using the Expectation Maximization (EM) algorithm as in Doz et al. (2012). The algorithm consists of two steps. In the first step (the M-step), the algorithm is initialized by computing principal components, and the model parameters are estimated by an OLS regression that treats the principal components as if they were the true common factors. This is a reasonable initialization since principal components have been proved to be an asymptotically consistent estimator of the true common factors when the cross-section dimension is large (see, Forni et al., 2000; Stock and Watson, 2002a,b; Bai, 2003). Once we have estimated parameters, the second step updates the estimate of the common factors by using the Kalman smoother. If we stop here, we get the two-step estimates of the common factors studied by Doz et al. (2011). Maximum likelihood is obtained by iterating the two steps until convergence, at each step taking into account the uncertainty related to the fact that factors are estimated.

A growing body of research has applied the quasi-maximum likelihood estimator to extract common factors from large cross-sections for a variety of empirical applications. For instance, this method has become a popular tool for now-casting (see, Banbura, Giannone and Reichlin, 2011; Banbura, Giannone, Modugno and Reichlin, 2013; Luciani, 2014). Banbura, Giannone and Lenza (2015) applied this approach to perform conditional forecasts and scenario analysis; Brave and Butters (2011) constructed a high-frequency indicator of national financial conditions published by the Federal Reserve Bank of Chicago. This method has also been used for structural analysis, as was done, for example, in Reis and Watson (2010) and Luciani (2015).

2.3 How many factors?

We begin our analysis by estimating common and block-specific components using likelihood-based methods described in the previous section. The factor estimates are computed using the commodity returns in x_t which exclude the higher-level aggregates represented by the commodity indices. In this way, we avoid introducing - by construction - collinearity in the panel data given that commodity indices are linear combinations of commodity prices.

We determine the number of blocks to include in the model by following the structure of our database. In macro-econometrics, data are typically organized either by country, sectoral origin or economic concept. Therefore the empirical literature on factor models has mostly looked at the composition of the data set for guidance on the extraction of the blocks. For instance, Forni and Reichlin (2001) distinguish between European and national components to study the potential degree of output stabilization deriving from national policies; using Bayesian estimation methods, Kose, Otrok, and Whiteman (2003) study the sources of the international business cycle by extracting world, country and regional components; Banbura, Giannone and Reichlin (2011) use blocks of nominal and real variables for the purpose of now-casting real economic activity; Miranda-Agrippino and Rey (2015) decompose fluctuations in risky assets into global, regional and asset-specific components. Like those authors, we extract local factors that reflect the composition of the panel data which in our case is based on different commodities categories. Therefore, we extract two main block factors (non-fuel and fuel), two sub-block factors (food and beverages and industrial inputs) and finally, five group factors (food, beverages, agricultural raw materials, metals and oil) (Table 1).

To determine the optimal number of common factors from the observed data, we take into account the trade-off between the goodness-of-fit and the loss in parsimony that arises from increasing the number of factors. To do so, we use a modified version of the information criterion in Bai and Ng (2002). They derive a penalty function to select the optimal number of factors in approximate factor models when factors are estimated by principal components. Nevertheless, their statistical approach can be extended to any consistent estimator of the factors provided that the penalty function is derived from the correct convergence rate.

For the quasi-maximum likelihood estimator used in this paper, Doz et al. (2012) show that the convergence rate for the factor estimates is given by $C^{*2}_{nT} = min\left\{\sqrt{T}, (n/(log(n))\right\}$. Hence, a modified version of the Bai and Ng (2002) information criterion (IC) is given by:

$$IC^{*}(r) = log(V(r, F_{(r)})) + rg(n,T),\; g(n,T) = ((log(C^{*2}_{nT}))/(C^{*2}_{nT}))$$

where r is the number of common factors, T is the number of sample observations, $F_{(r)}$ denotes the estimated factors, $V(r, F_{(r)})$ is the sum of squared idiosyncratic components divided by nT and $g(n, T)$ represents the penalty function for over-fitting.[2] For our panel data, the statistics in Table 3 indicates that the model with one common factor provides the smallest value for the IC statistic. From here on, we will refer to this single common factor in commodity prices as the global factor.

2.4 Empirical results

The global factor

The global factor estimated over the full sample is shown in Figure 1 along with the IMF global index of commodity prices. The latter is a linear combination of commodity prices with weights given by trade values. While cross-sectional averages, such as the IMF index, tend to approximate well the global factor in the case of limited cross-correlation among idiosyncratic disturbances (see, Forni and Reichlin, 1998), in practical applications, simple averages may have a substantial component of noise arising from the idiosyncratic component. As Figure 1 illustrates, the global factor and the IMF broad index of commodity prices resemble each other,[3] but their second-order properties appear to be different. A visual inspection of the two series suggests that while the broad index of commodity prices is characterized by swift fluctuations, for instance those associated with the oil price shocks in the early 1990s, the global factor is a smoother and more persistent series.

Particular attention should clearly be paid to what the global factor captures. A natural conjecture is that, as a pervasive shock affecting a large cross-section of commodity prices, the global factor might be capturing shifts in the demand for commodities associated with the global business cycle. In fact, as the global economy expands, so does demand for a broad group of commodities, directly via the impact on industrial commodities and indirectly via general equilibrium effects. Barsky and Kilian (2002) argued that broad-based variations in commodity prices are consistent with the evidence of a shift in demand driven by macroeconomic conditions. If so, one would expect the global factor to have homogenous effects on all commodity markets and therefore, limited effects on relative prices. This is confirmed by the evidence in Figure 2 that shows that the factor loadings associated with the global factor are mostly positive. Because stronger economic activity is associated with higher commodity prices, it is not surprising that the global factor is also strongly correlated with indicators of global real economic activity. To illustrate this, Figure 3 compares the global factor with the Kilian's index of global real economic activity (Kilian, 2009). Kilian's index, based on percentage changes of dry cargo ocean freight rates, has been developed to capture shifts in the demand for industrial commodities associated with periods of high and low real economic

[2] The information criterion has been recently applied to the quasi-maximum likelihood estimator by Coroneo et al (2016).

[3] The correlation coefficient between the two series is 0.63.

activity. To make the comparison meaningful, we expressed the global factor in year-on-year growth rates. As Figure 3 shows, the two indices are positively correlated and follow the major expansion and contraction phases in the international business cycle over the period considered with the largest declines following recessions. For example, both measures capture the fast macroeconomic expansion that characterized the world economy and, in particular some emerging market economies, from 2003 to 2007. Moreover, both of the them declined in the second half of 2014, suggesting a weakening in global economic activity which is then reflected in the subsequent decline in the price of oil. Likewise, Figure 4 shows that the global factor is also strongly correlated with monthly indicators of industrial production. As noted by Kilian (2017), the common factors or broad-based indices of commodity prices are actually leading indicators with respect to global industrial production, which makes the global factor a suitable real-time indicator of to estimate aggregate demand pressures in structural models.

To gauge the extent to which the global factor is related to fluctuations in oil prices, Figure 5 shows the global factor with the growth rate of the price of Brent crude oil together with estimates of global demand and supply of oil. Three observations can be made. First, the correlation between the global factor and oil prices is only mildly positive over the full sample although it has increased substantially since the last decade. Second, both the global factor and the price of oil are positively correlated with measures of world consumption of oil. Third, the spikes in the price of oil that coincided with some exogenous events in the oil market (the Persian Gulf War and the Venezuela crisis and the Iraq invasion in 2003), are not associated with similar variations in the global factor. Rather, these price spikes appear to be associated with important negative changes in the supply of oil.

As a robustness check, we estimate the model using real commodity prices (i.e. deflated by the US CPI). The global factor (as shown in Figure 6) does not appear to be particularly sensitive to this transformation. This result might reflect the fact that our sample does not include high-inflation periods, such as the Great inflation of the 1970s.

Sources of commodity price fluctuations

In this section we study the relative importance of global and block-specific factors in explaining commodity price fluctuations (tables 4 and 5). For expository purposes, we also compute a model-based variance decomposition for the commodity indices in our dataset.[4]The global factor explains more than two-thirds of the variations of the index in the index of non-fuel commodities. This stems from the fact that a large fraction of the variance of food commodities and metals is captured by the global factor. In particular, the global factor explains almost half of the variations in soybean and soybean oil, 40 percent of sunflower oil and

[4]Let y_t be an m-dimensional vector of commodity indices and W be a given $(m \times n)$ matrix of weights used to compute the indices. Then, the variance-covariance matrix of y_t is $\Sigma_y = W\Lambda\Sigma_f\Lambda\prime W\prime + W\Sigma_e W\prime$ where Σ_f and Σ_e are the variance-covariance matrices of the factors and idiosyncratic components, respectively.

about one-third of copper and palm oil price variations. The strong common component in the price of these commodities and in particular copper, explains why researchers have used changes in the price of copper or in a broad index of non-fuel commodity prices to isolate global demand components (Kilian and Lewis, 2011; Hamilton, 2014). By contrast, the bulk of the fluctuations in beverages, agricultural raw materials and fuel prices is mostly captured by block-specific factors. Nevertheless, the global factor explains about 20 percent of energy and oil price fluctuations. Given the large weight attributed to oil prices in the IMF index, the fuel-specific factor explains most of the variance of the overall IMF index of commodity prices while one-third of its fluctuations are driven by the global factor.

To check the robustness of these results, we include a second global factor in the model. The results shown in Figure 7 and 8 indicate that the second common factor explains only a very small share of the variance of commodity prices on average. This fraction is small enough to reinforce the evidence provided by the IC statistic about the presence of a single global factor.

Sub-sample analysis

The analysis over the full sample might mask some important changes that might have occurred in the commodity markets, especially since the start of the commodity price boom in mid-2003. To check that possibility, we conducted a model-based decomposition of the variance in all the commodity price indices over two sub-samples. We use 2003 as a break date in line with the observed increase in commodity prices. The sub-sample analysis confirms that the global factor explains an important fraction of the variation of non-fuel commodities before 2003 whereas block-specific and idiosyncratic components account for the whole variation in oil prices in the first sub-sample. This evidence suggests that commodity-specific shocks were, on average, a more important determinant of the price of oil than global demand shocks in the first part of the sample. The structural VAR analysis in Kilian and Murphy (2014) supports this interpretation. Their work shows that key historical events in the oil market over this period, such as the collapse of the OPEC cartel in 1986, the Persian Gulf war in 1990-91 and the Venezuela crisis in 2002, mostly reflected shocks to the speculative demand for oil together with supply shifts. The decomposition estimated over the second sub-sample indicates that the importance of the global factor has increased remarkably since 2003 for oil and metals for which the share of the variance explained by the global factor increased to 40 and 60 percent, respectively. As a result, the share of the variance of the IMF index that can be attributed to the global factor has also increased from less than 10 percent to 60 percent in the period starting in 2003.

Historical decompositions of commodity price changes

As sustained changes in the global factor tend to be indicative of aggregate demand pressures, our factor-structure approach, although it is not structural in nature, allows to disentangle demand-driven commodity price fluctuations that are associated with the global business cycle from those that are commodity-specific, such as supply-driven fluctuations. Commodity-specific shocks are unlikely to spill over to other commodities and their effects are likely to be confined to their specific market or to markets of commodities in their category. In our model their effects will not show up in the common component but in the idiosyncratic and block-specific factors. As discussed in previous sections, a clear advantage of the block structure is that it obviates any need to carefully select the commodities that enter the factor model as practiced in Alquist and Coibion (2014) and discussed in Kilian (2017). To keep the panel balanced and avoid over-representation of some categories which could bias the estimates of the factors toward some markets, Alquist and Coibion (2014) extract a common factor from a restricted group of commodities that are supposedly unrelated. Rather than selecting the variables before estimation, our approach uses a block structure to mitigate this issue.

In addition, local factors can be confused with global variations in the absence of a block structure. To illustrate this, we compare the estimated global and block factors of our benchmark specification (M_1) with three common factors extracted from a factor model in which the local correlation among idiosyncratic components (M_2) is not modeled (Figure 10). The first common factors of the two models are very much alike. The second common factor in M_2 is akin to the Non-Fuel block in M_1. The third factor of M_2 is highly correlated with the fuel block in M_1 and, to some extent, with the food and beverages sub-block.

In what follows we review a few key historical episodes of commodity price variation in our sample through the lens of our model. The model allows the analysis of a large panel of commodity prices, but for reasons of space we focus on an arbitrary and small number of commodities with large trading volume. An important event in the commodity markets was the run-up in commodity prices from 2003 to mid-2008. Numerous studies have found that the fast economic expansion of China and other emerging market economies, caused the surge in prices (see, Hamilton, 2009; Kilian and Hicks, 2013; Aarsveit et al., 2014). A decomposition of the price of oil indicates that the cumulative effect of shifts in the global factor largely explains the oil price surge after 2003, while the fuel-specific component had a smaller role (Figure 11, top left panel). This result is consistent with estimates from empirical models of the global oil market, which attributed the bulk of the cumulative increase in the price of oil to global demand shocks (Kilian, 2009; Baumeister and Peersman, 2013; Kilian and Murphy, 2014). Fuel-specific components were important to explain the increase in the price of oil in the early 2000s, also in line with previous estimates. For non-fuel commodity prices, the global factor is by far the most important determinant of the surge (Figure 11, top right panel and bottom panels), suggesting that commodity prices responded to the same economic fundamentals in that period.[5]

We consider four historical episodes in the oil market (Figure 12). The first two are the oil price decline that followed the collapse of the OPEC cartel in late 1985 and the oil price spike that occurred in response to the Iraqi invasion of Kuwait in 1990. These can be viewed as examples of price variations that are driven by factors specific to the oil market and unrelated to changes in macroeconomic conditions. The historical decomposition shows that, in both episodes, fuel-specific factors were the main underlying sources of oil price changes that occurred before 2000, while the global factor clearly had no role (Figure 12, top panels). This is consistent with evidence from structural models of the oil market that showed that shifts in the inventory demand and in the supply of oil were the most important determinant of the oil price in both episodes. The other two episodes, the price decline that started in mid-2008 as a result of the contraction in world economic activity and the decline beginning in the second half of 2014. The drop starting in mid-2008 is mostly explained by the global factor (Figure 12, bottom left panel). There is also evidence that the oil-specific component exerted further downward pressures on the price of oil since the end of 2008. Regarding the decline from mid-2014 to end-2015, an initial assessment by Baumeister and Kilian (2016) found that global demand was the main cause of the decline from June to December 2014. We find that while the global factor explains most of the initial drop, cumulative changes in the fuel-specific component explain most of the variations since the end of 2014. Thus, the model attributes about one-third of the oil price fall from June 2014 to December 2015 to the global factor (Figure 12, bottom right panel). The increasing relevance of fuel-specific components since the end of 2014 coincides with the decision of OPEC in November 2014 to hold production unchanged in order to put downward pressure on prices. The empirical findings in Baffes et al. (2015) and Groen and Russo (2015) appear to be consistent with ours.

3 Predictive content of the global factor

A growing empirical literature has used factor models estimated on panels of commodity prices for forecasting purposes. Common factors have been used to forecast commodity prices themselves (see, West and Wong, 2014; Poncela et al., 2015) or other macro-variables such as inflation (Gospodinov and Ng, 2013). Other empirical studies have investigated whether macroeconomic and financial data have predictive power for commodity prices (see, Chen,

[5]A different view expressed by some observers and by a few studies in the financial literature (e.g. Tang and Xiong, 2012), has associated the across-the-board surge in commodity prices in 2003-2008 with the growing participation of financial speculators in commodity markets at the beginning of the 2000s. A large body of research, however, has provided compelling evidence that financial speculation did not have an effect on commodity prices (e.g. Kilian and Murphy, 2014; Kilian and Lee, 2014; Juvenal and Petrella, 2014). For a survey of this literature, the reader is referred to Fattouh, Kilian and Mahadeva (2013).

Rogoff and Rossi, 2012; Groen and Pesenti, 2011). A strand of the literature focusing on the price of oil has found that proxies of global demand have predictive power for commodity prices (see, Baumeister and Kilian, 2012). Similarly, changes in the spot price of industrial raw materials have been shown to improve the forecast of the price of oil, as those price changes are more likely to capture shifts in the global demand for industrial commodities (see, Alquist, Kilian and Vigfusson, 2013).

In this section we perform an out-of-sample validation of the model to verify the robustness of our modeling strategy. Starting from January 2001, we compute out-of-sample forecasts of commodity prices each month from February 2001 to December 2015 using a rolling window of 20 years of past data. The h-step ahead forecasts for individual commodity prices are iterated from the state-space representation using the Kalman filter while forecasts for aggregate commodity indices are computed as averages of the individual commodity price forecasts, weighted by trade weights.[6] We first compute the sequence of differences in the out-of-sample forecast errors, comparing the model with a naive benchmark (i.e. a constant growth model). We then calculate the average loss difference as well as rolling average losses along the lines of the fluctuation test in Giacomini and Rossi (2010). This test, which is useful for studying the forecasting performance of a model in an unstable environment, is based on the difference between the mean squared forecast error (MSFE) of the candidate model and the benchmark, smoothed over time with a centered rolling window of fixed size. The statistical significance of the relative performance of the model against the benchmark is then tested at each point in time using the Diebold and Mariano (1995) test of equal predictive accuracy.

The main results of the out-of-sample forecasting exercise are as follows. First, the model performs well in predicting commodity prices and indices at short horizons. At $h = 1$, the model outperforms the benchmark with gains in accuracy that range from 18% for the non-fuel index to 12% for the fuel index (Table 6). The forecasts of disaggregated commodity prices (Table 7) indicate that the model provides the largest gains in accuracy for food and metals (for instance, copper (19%), rice (19%), poultry (46%), cotton (17%) and aluminum (12%)). However, at $h = 1$, the reduction in the MSFE is also notable for oil prices for which gains range between 9% and 12%. Second, the predictive performance deteriorates progressively over longer horizons. At $h = 12$, we cannot reject the null hypothesis of equal predictive performance between the model and the benchmark. Last, we find that the predictive ability of the model has changed over time. The evolution of the rolling relative MSFE in Figure 13 indicates that the predictability of oil and other energy commodities increased markedly in the second half of the period. Indeed, from 2007 to 2011, the MSFE of the factor model improved substantially compared with the benchmark. However, given the high level of volatility, the

[6] For each series, the variable that is predicted is $X^h_{i,t+h} = 100 \times ln(X_{i,t+h}/X_{i,t})$. The model is parametrized as in the previous sections, a single global factor, a single factor for block, sub-block and group of commodity prices and one lag in the factor VAR. We also provide the forecasting results for a model specified - as robustness check - with two global factors.

test cannot reject the null hypothesis of equal predictive accuracy. The finding of a better predictive performance during the Great Recession is consistent with previous results showing that, for macroeconomic and financial variables, downturn periods are characterized by increased co-movement (see, D'Agostino and Giannone, 2012).

4 Concluding remarks

We studied the co-movement in international commodity returns by analyzing a broad range of commodities, that are representative of the global market. Our results indicate that co-movement is not only as strong as documented by Pindyck and Rotemberg (1990) but it has been also strengthening since the beginning of the 2000s. Contrary to earlier studies, however, we find that the co-movement is neither excessive nor puzzling. Instead, it is driven by a pervasive factor that is strongly related to measures of global economic activity, which suggests that the factor is closely linked to demand determinants.

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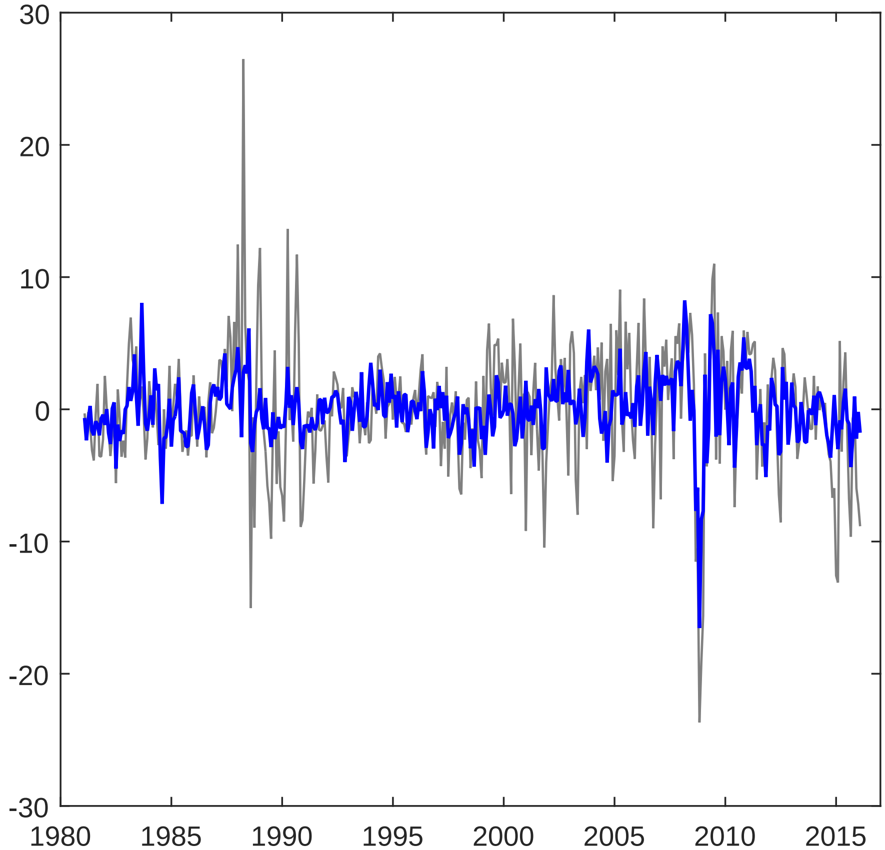
Figure 1: The global factor



Note: The figure shows the estimated global factor (blue line) and the IMF index of commodity prices (gray line).

Figure 2: Factor loadings associated with the global factor

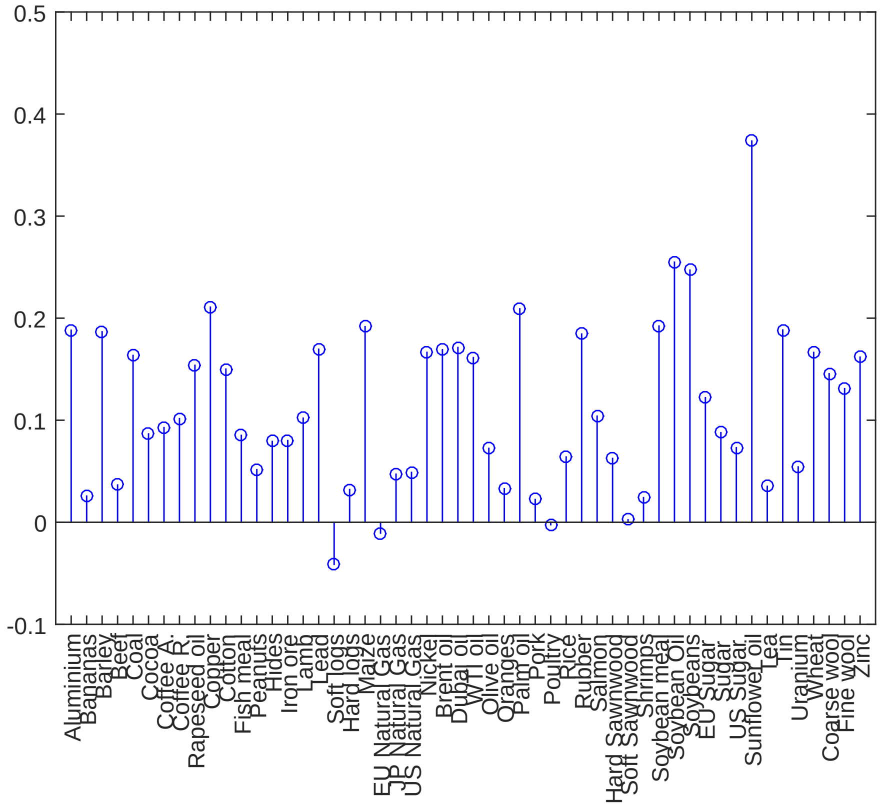
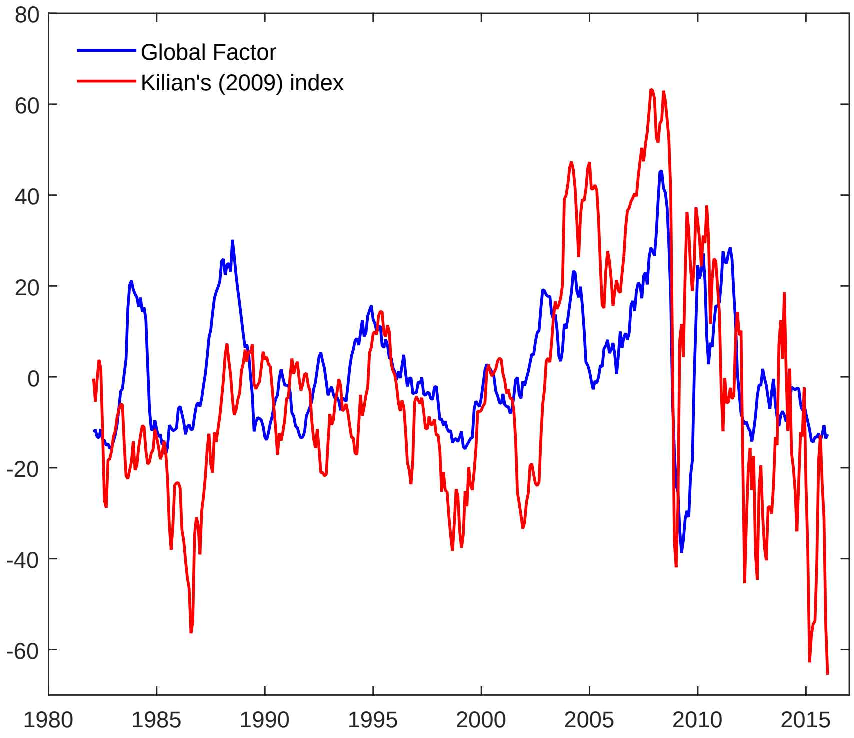
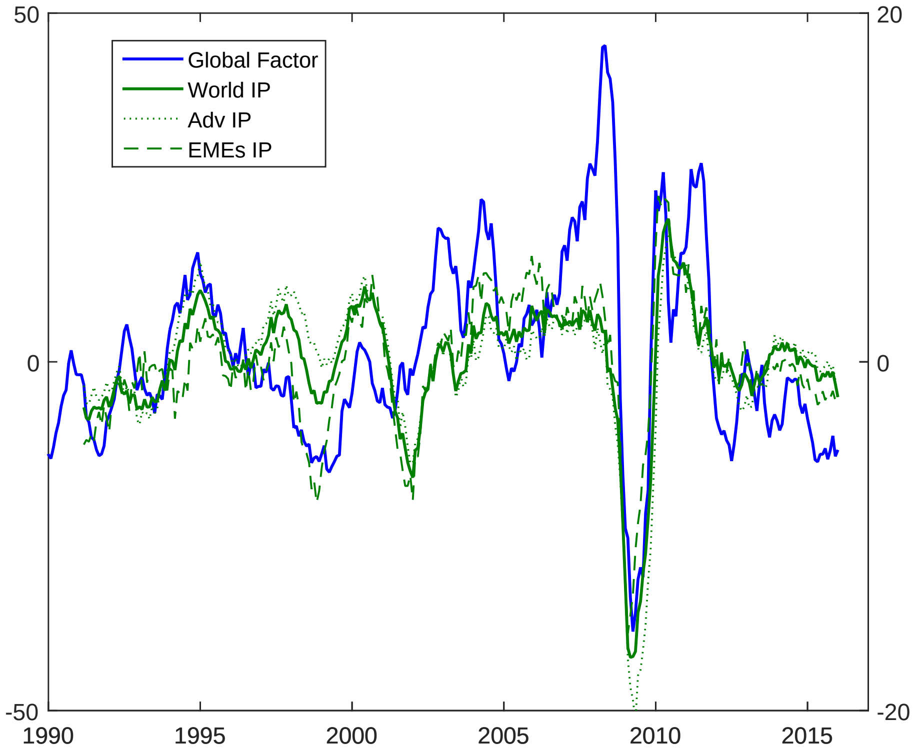


Figure 3: The global factor and the Kilian's index of real economic activity



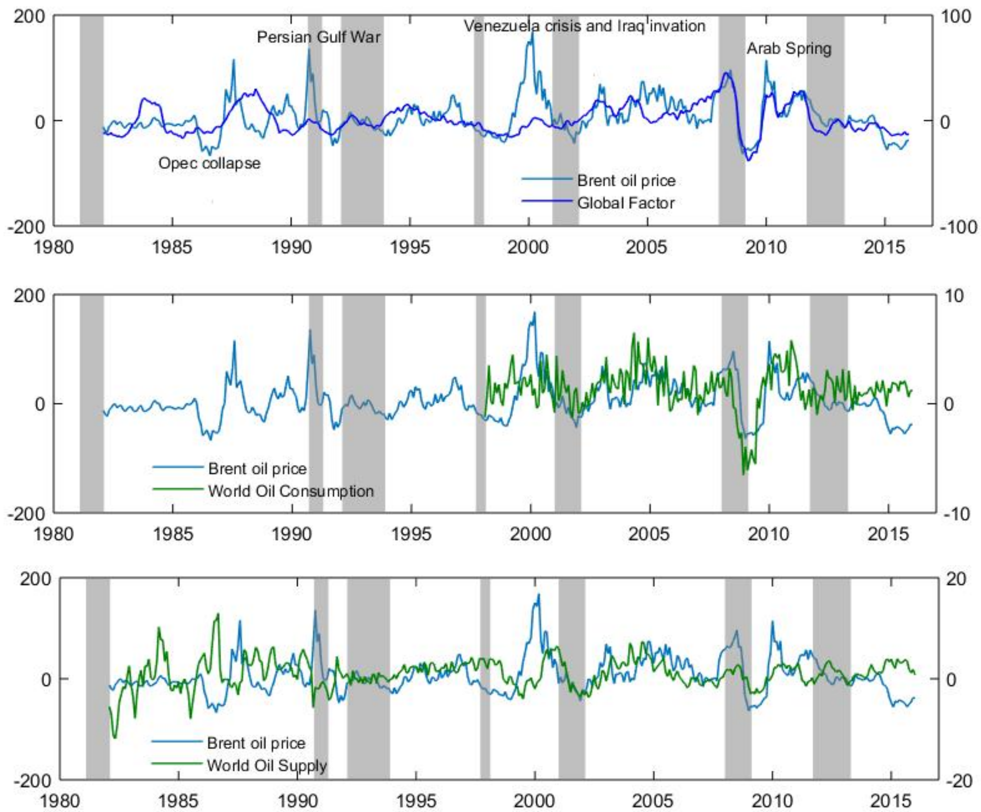
Note: The figure plots the global factor (blue line) and the Kilian (2009) index of real economic activity (red line). The global factor is expressed in year-on-year growth rates.

Figure 4: The global factor and industrial production indices



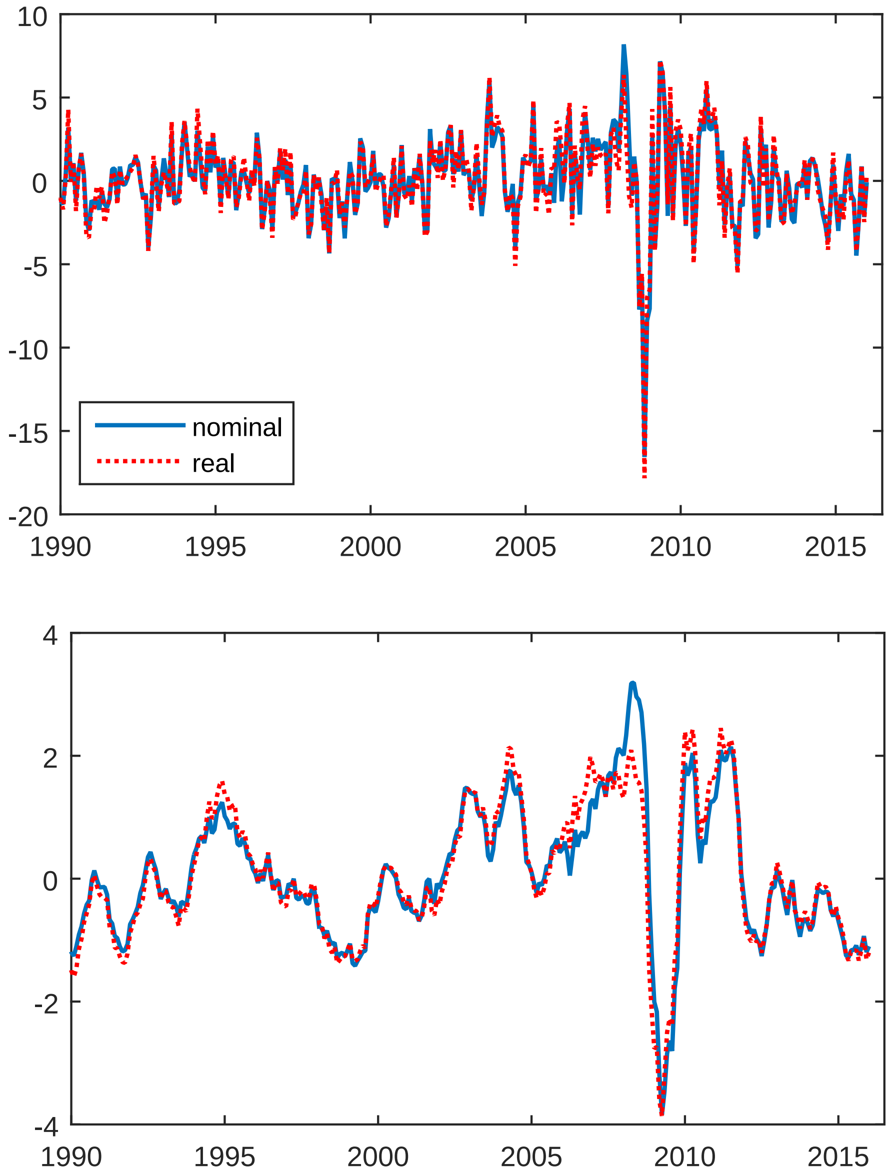
Note: The figure plots the estimated global factor (blue line) and measures of industrial production in selected areas as provided by the CPB Netherlands Bureau for Economic Policy Analysis. All variables are expressed in year-on-year growth rates.

Figure 5: Oil and the Global Factor



Note: All variables are expressed in year-on-year growth rates. Estimates for the world oil consumption are taken from Short-Term Energy Outlook of the Energy Information Administration (EIA) while the world crude oil production is taken from the Monthly Energy Review of EIA. The vertical bars represent periods of widespread economic slowdown. In particular, we include the early 1980s and 1990s recessions, the Asian financial crisis of 1997–1998, the recession that followed the bursting of the dot-com bubble in the 2000s, the Great Recession and, the euro area recession in 2011-2013.

Figure 6: The global factor extracted from real commodity prices



Note: The upper panel of the figure reports the estimated global factor extracted from real commodity prices (US CPI deflated). The lower panel compares the nominal and the real global factor expressed in year-on-year growth rates.

Figure 7: Variance explained by the first two global factors

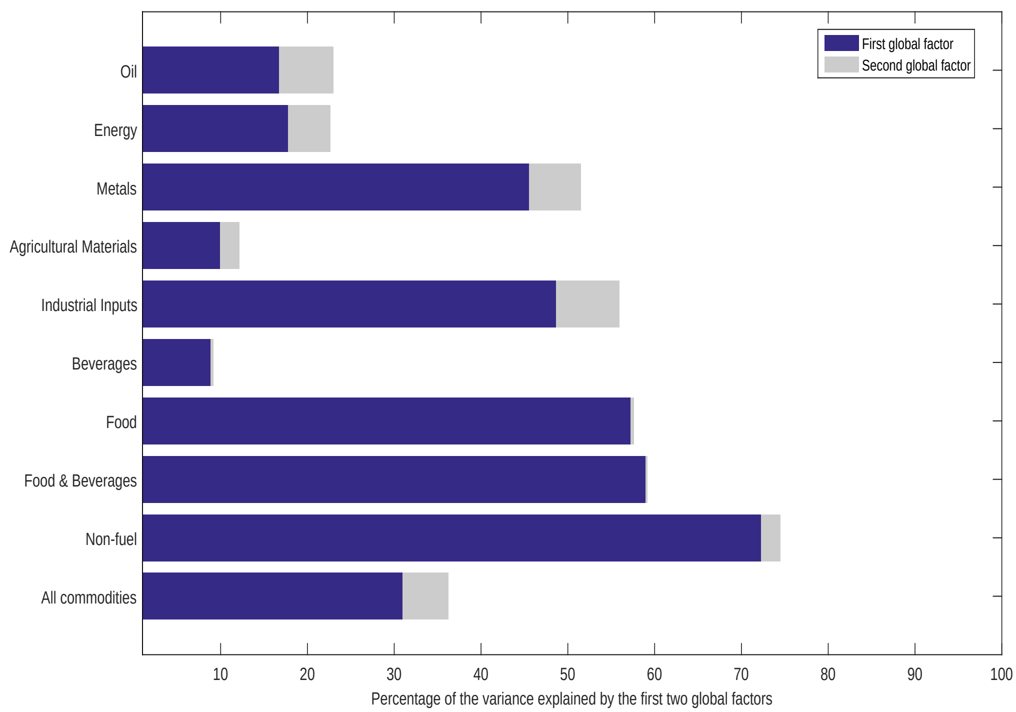


Figure 8: Variance explained by the first two global factors

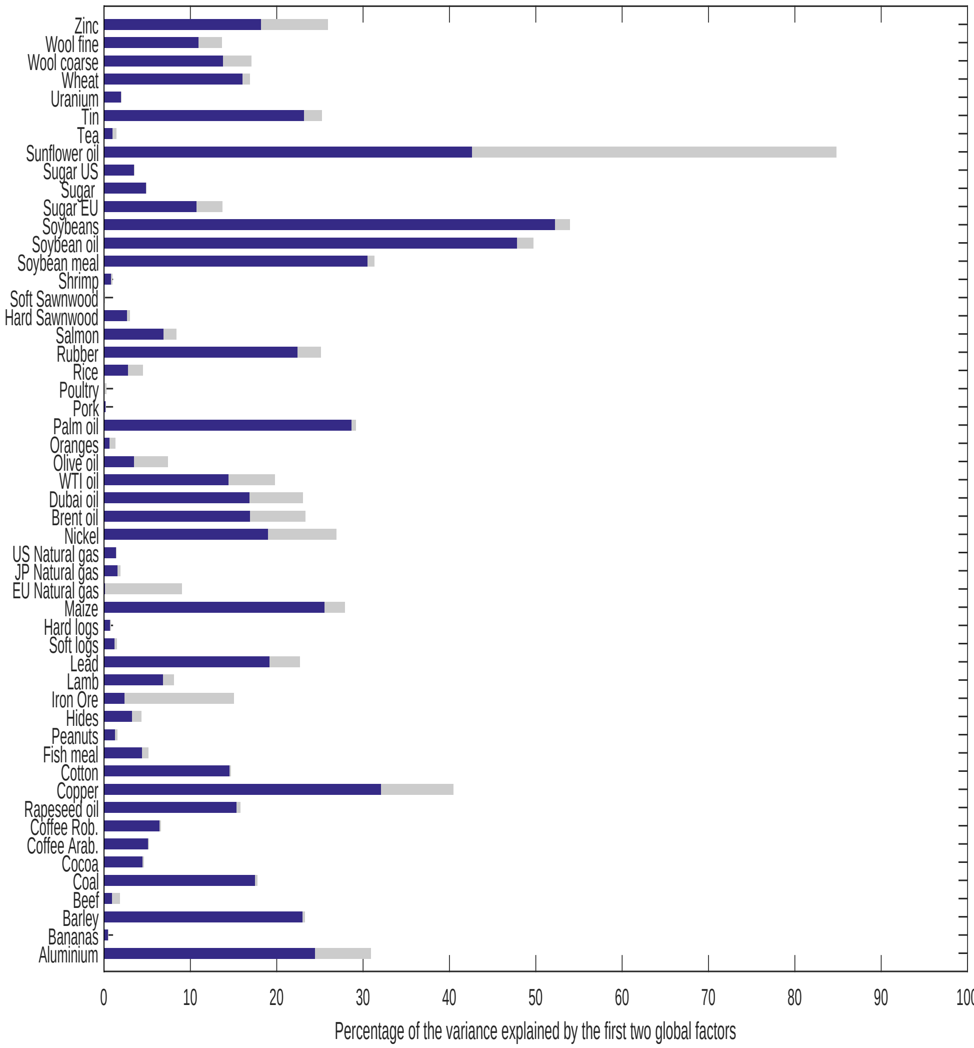
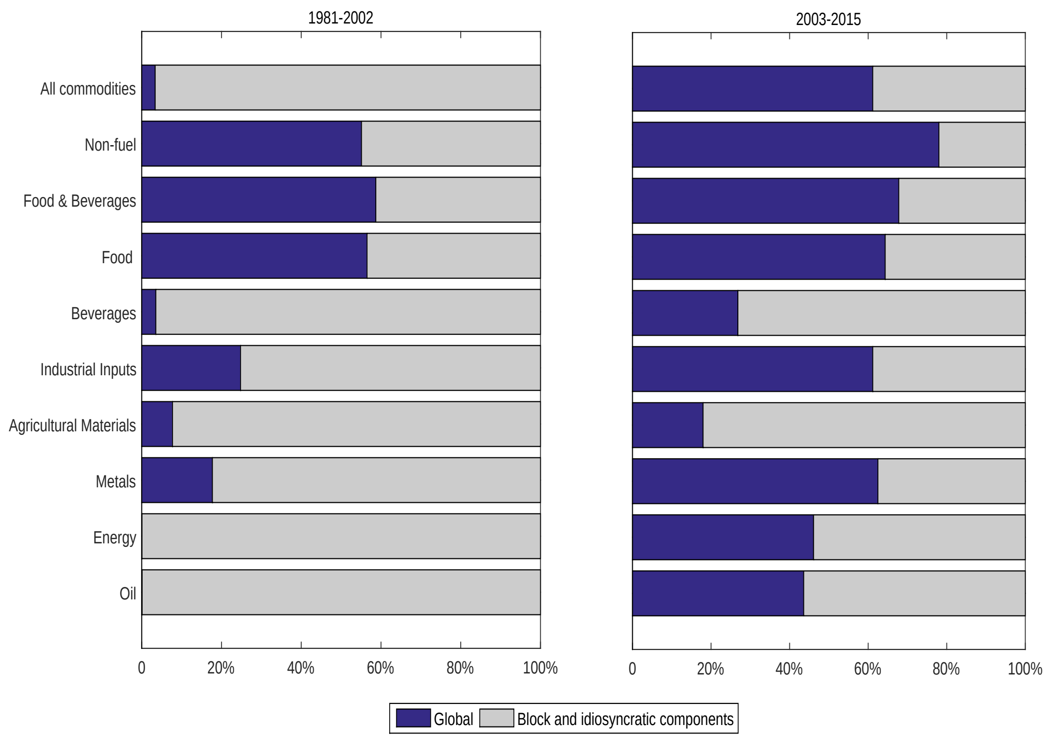
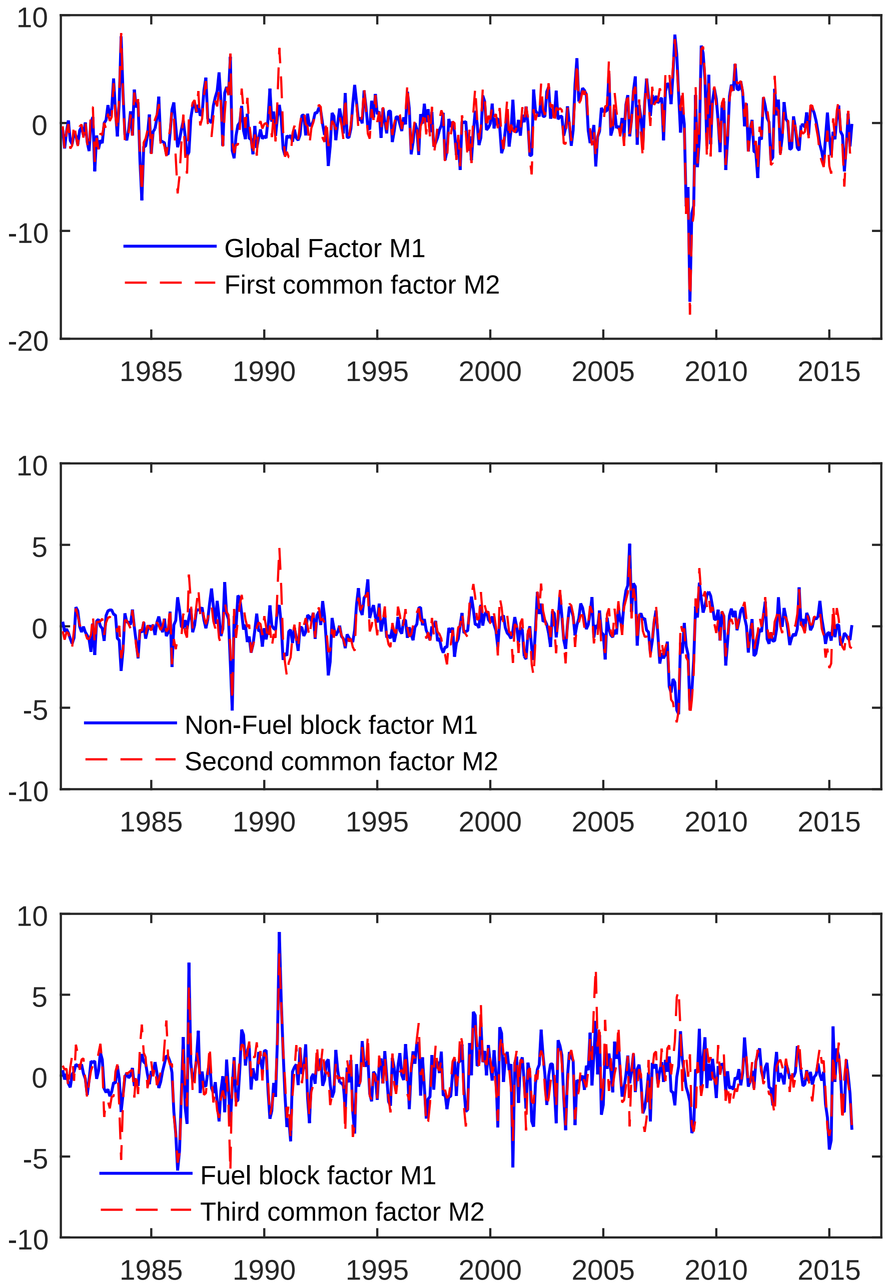


Figure 9: Variance decomposition: sub-sample analysis



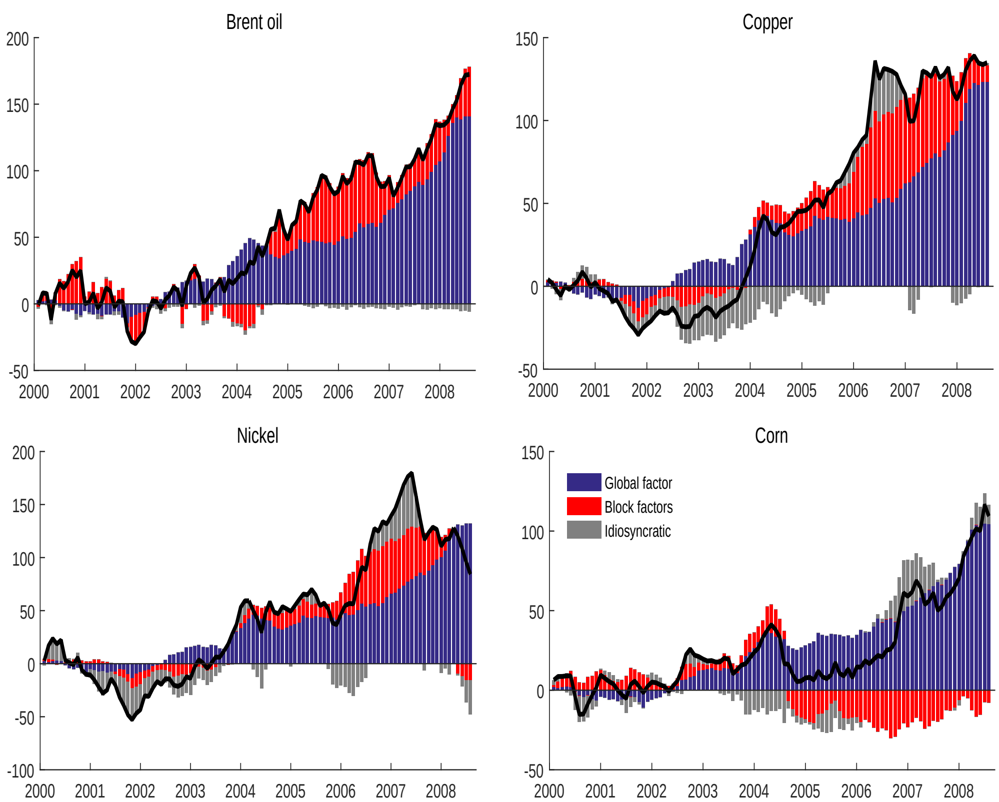
Note: The figure reports the variance decomposition of commodity price indices over two sub-samples. The share of the variance explained by the global factor is captured by the blue bar. The gray bar is the percentage of the variance explained by block-specific and idiosyncratic components. The first sub-sample goes from Jan. 1981 to Dec. 2002; the second goes from Jan. 2003 to Dec. 2015.

Figure 10: Block factors and weak common factors



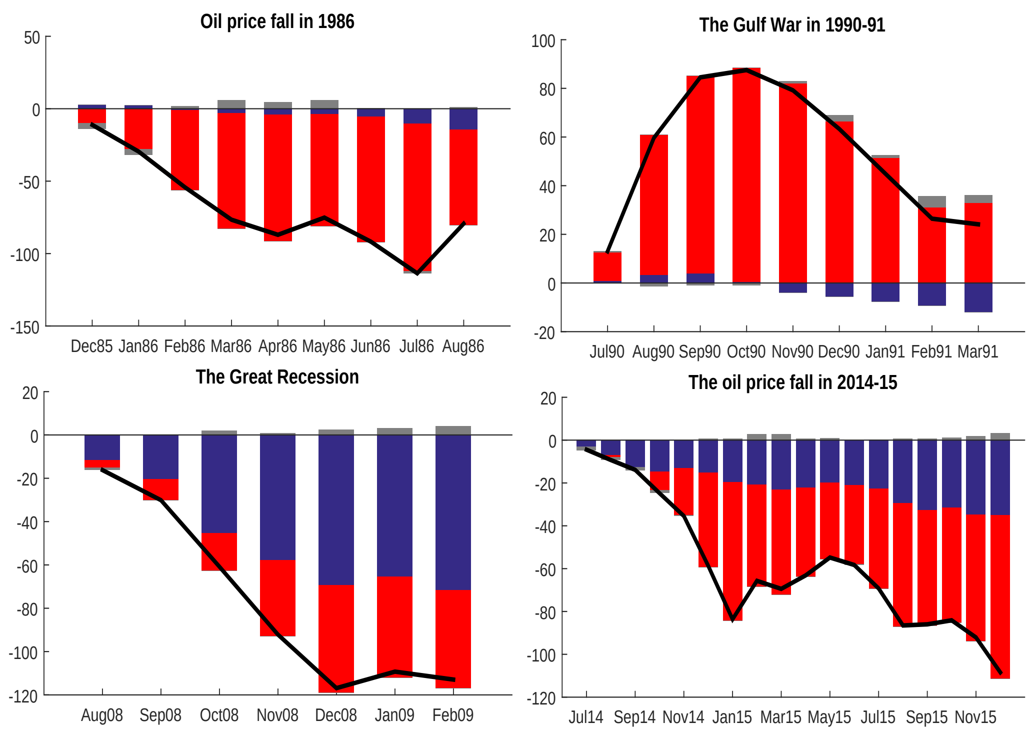
Note: The figure compares the the estimated global and block factors (Non-Fuel and Fuel) of our benchmark specification (M_1) with the first three common factors extracted from a factor model that does not have a block structure for the idiosyncratic components (M_2).

Figure 11: Historical decompositions of commodity prices



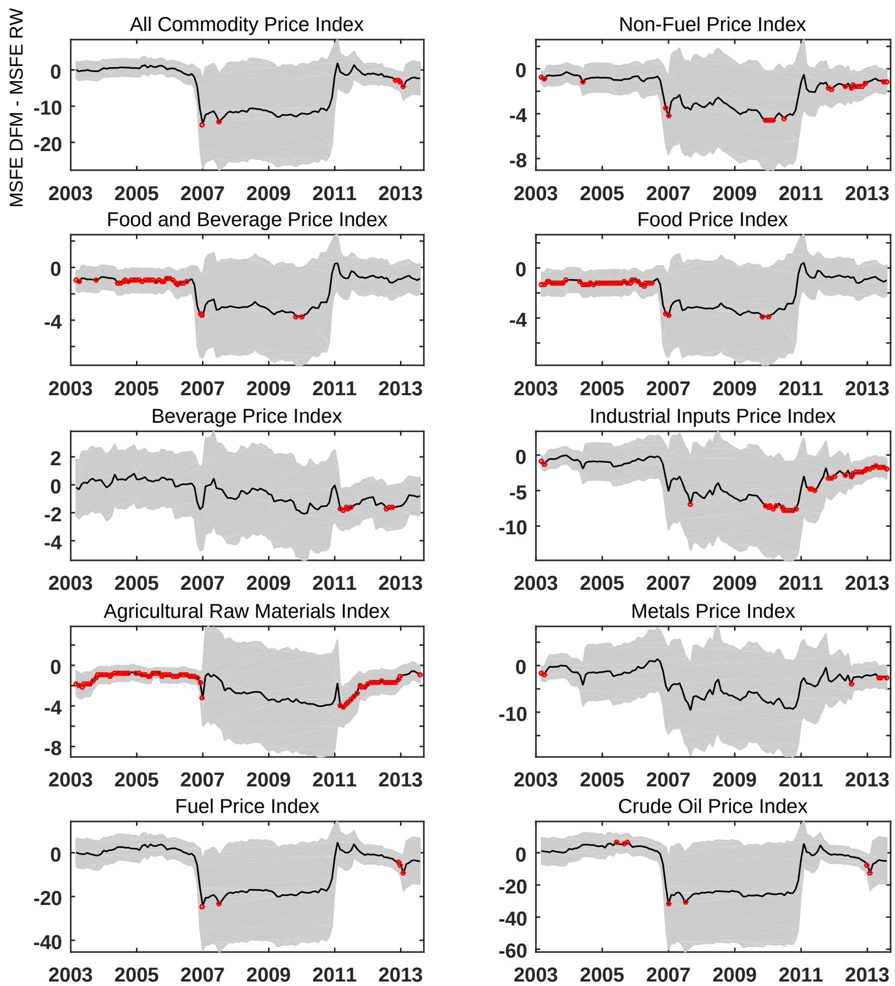
Note: The figure reports the historical decomposition of the price for a selected group of energy, metal and food commodities, showing the cumulative effects at each point in time of global (blue), block-specific (red) and idiosyncratic (gray) shocks from January 2000 to July 2008.

Figure 12: Historical decompositions of the price of oil in selected episodes



Note: The figure presents the historical decomposition of the price of oil, showing the cumulative effects at each point in time of global (blue), block-specific (red) and idiosyncratic shocks (gray) during four historical episodes of large oil price variations.

Figure 13: Time-varying predictability



Note: The figure shows the difference between the MSFE of the factor model and the MSFE of the benchmark, smoothed over time with a centered rolling window spanning 4 years. A negative number indicates that the factor model has a higher predictive accuracy than the benchmark. The 90% confidence bands are represented by the shaded area and are derived from testing the null hypothesis of equal predictive accuracy at each point in time. Red circles indicate rejection of the hypothesis of equal predictive accuracy at the 5% level.

Table 1: Structure of the database

Global	Blocks	Sub-blocks	Groups	N. Series	Share (in %)
All commodities				52	
	Non-Fuel			45	36.9
		Food & Beverages		28	18.5
			Food	24	16.7
			Beverages	4	1.8
		Industrial Inputs		17	18.4
			Agricultural Raw Materials	9	7.7
			Metals	8	10.7
	Energy			7	63.1
			Oil	3	53.6

Table 2: Data description

Mnemonic	Unit	description	IMF global commodity index 2002-2004 weights
PALLFNF	Index	All Commodity Price Index, 2005 = 100, includes both Fuel and Non-Fuel	100.0
PNFUEL	Index	Non-Fuel Price Index, 2005 = 100, Food and Beverages and Industrial Inputs	36.9
PFANDB	Index	Food and Beverage Price Index, 2005 = 100, Food and Beverage	18.5
PFOOD	Index	Food Price Index, 2005 = 100, Cereal, Vegetable Oils, Meat, Seafood, Sugar, Bananas, Oranges	16.7
PBEVE	Index	Beverage Price Index, 2005 = 100, Coffee, Tea, Cocoa	1.8
PINDU	Index	Industrial Inputs Price Index, 2005 = 100, Agricultural Raw Materials and Metals	18.4
PRAWM	Index	Agricultural Raw Materials Index, 2005 = 100, Timber, Cotton, Wool, Rubber, Hides	7.7
PMETA	Index	Metals Price Index, 2005 = 100, Copper, Aluminium, Iron Ore, Tin, Nickel, Zinc, Lead,Uranium	10.7
PNRG	Index	Fuel (Energy) Index, 2005 = 100, Crude oil , Natural Gas, Coal	63.1
POILAPSP	Index	Crude Oil (petroleum), Price index, 2005 = 100, simple average of Brent, WTI, Dubai Fateh	53.6
PALUM	USD	Aluminium, 99.5% minimum purity, LME spot price, CIF UK ports, USD per metric ton	3.9
PBANSOP	USD	Bananas, Central American and Ecuador, FOB U.S. Ports, USD per metric ton	0.4
PBARL	USD	Barley, Canadian no.1 Western Barley, spot price, USD per metric ton	0.3
PBEEF	USD	Beef, Australian and New Zealand 85% lean fores, CIF U.S. import price, US cents per pound	1.4
PCOALAU	USD	Coal, Australian thermal coal, 12,000- btu/pound, FOB Newcastle/Port Kembla, USD(metric ton)	2.6
PCOCO	USD	Cocoa beans, Int. Cocoa Org. cash price, CIF US and European ports, USD per metric ton	0.7
PCOFFOTM	USD	Coffee, Other Mild Arabicas, Int. Coffee Org. NY cash price, US cents per pound	0.5
PCOFFROB	USD	Coffee, Robusta, Int. Coffee Org. NY cash price, US cents per pound	0.4
PROIL	USD	Rapeseed oil, crude, fob Rotterdam, USD per metric ton	0.3
PCOPP	USD	Copper, grade A cathode, LME spot price, CIF European ports, USD per metric ton	2.8
PCOTTIND	USD	Cotton,Outlook 'A Index', Middling 1-3/32 inch staple, CIF Liverpool, US cents per pound	0.7
PFISH	USD	Fishmeal, Peru Fish meal/pellets 65% protein, CIF, USD per metric ton	0.2
PGNUTS	USD	Groundnuts (peanuts), 40/50 , cif Argentina, USD per metric ton	0.2
PHIDE	USD	Hides, Heavy native steers, over 53 pounds, wholesale price, US, Chicago, US cents per pound	2.6
PIORECR	USD	China import Iron Ore Fines 62% FE spot (CFR Tianjin port), US dollars per metric ton	1.3
PLAMB	USD	Lamb, frozen carcass Smithfield London, US cents per pound	0.3
PLEAD	USD	Lead, 99.97% pure, LME spot price, CIF European Ports, USD per metric ton	0.2
PLOGORE	USD	Soft Logs, Average Export price from the U.S. for Douglas Fir, USD per cubic meter	0.4
PLOGSK	USD	Hard Logs, Best quality Malaysian meranti, import price Japan, USD per cubic meter	0.4
PMAIZMT	USD	Maize (corn), U.S. No.2 Yellow, FOB Gulf of Mexico, U.S. price, USD per metric ton	1.0

PNGASEU	USD	Natural Gas, Russian Natural Gas border price in Germany, USD per thousands of cubic meters of gas	3.2
PNGASJP	USD	Natural Gas, Indonesian Liquefied Natural Gas in Japan, USD per cubic meter of liquid	1.9
PNGASUS	USD	Natural Gas, Henry Hub terminal in Louisiana, USD per thousands of cubic meters of gas	1.9
PNICK	USD	Nickel, melting grade, LME spot price, CIF European ports, USD per metric ton	1.1
POILBRE	USD	Crude Oil (petroleum), Dated Brent, light blend 38 API, fob U.K., USD per barrel	17.9
POILDUB	USD	Oil; Dubai, medium, Fateh 32 API, fob Dubai Crude Oil, Dubai Fateh Fateh 32 API, USD per barrel	17.9
POILWTI	USD	Crude Oil (petroleum), West Texas Intermediate 40 API, Midland Texas, USD per barrel	17.9
POLVOIL	USD	Olive Oil, extra virgin less than 1% free fatty acid, ex-tanker price U.K., USD per metric ton	0.3
PORANG	USD	Oranges, miscellaneous oranges CIF French import price, USD per metric ton	0.5
PPOIL	USD	Palm oil, Malaysia Palm Oil Futures (first contract forward) 4-5 percent FFA, USD per metric ton	0.7
PPORK	USD	Swine (pork), 51-52% lean Hogs, U.S. price, US cents per pound	1.1
PPOULT	USD	Poultry (chicken), Whole bird price, Ready-to-cook, whole, iced, Georgia, US cents per pound	0.9
PRICENPQ	USD	Rice, 5 percent broken milled white rice, Thailand nominal price quote, USD per metric ton	0.6
PRUBB	USD	Rubber, Singapore Commodity Exchange, No. 3 Rubber Smoked Sheets, 1st contract, US cents-pound	0.5
PSALM	USD	Fish (salmon), Farm Bred Norwegian Salmon, export price, USD per kilogram	2.5
PSAWMAL	USD	Hard Sawnwood, Dark Red Meranti, select and better quality, C&F U.K port, USD per cubic meter	0.8
PSAWORE	USD	Soft Sawnwood, average export price of Douglas Fir, U.S. Price, USD per cubic meter	1.8
PSHRI	USD	Shrimp, No.1 shell-on headless, 26-30 count per pound, Mexican origin, NY port, US cents-pound	0.7
PSMEA	USD	Soybean Meal, Chicago Soybean Meal Futures Minimum 48 percent protein, USD per metric ton	0.8
PSOIL	USD	Soybean Oil, Chicago Soybean Oil Futures exchange approved grades, USD per metric ton	0.4
PSOYB	USD	Soybeans, U.S. soybeans, Chicago Soybean futures contract No. 2 yellow and par, USD per metric ton	1.2
PSUGAEEC	USD	Sugar, European import price, CIF Europe, US cents per pound	0.2
PSUGAISA	USD	Sugar, Free Market, CSCE contract n.11, US cents a pound	0.6
PSUGAUSA	USD	Sugar, U.S. import price, contract no.14 nearest futures position, US cents a pound	0.1
PSUNO	USD	Sunflower oil, Sunflower Oil, US export price from Gulf of Mexico, USD per metric ton	0.2
PTEA	USD	Tea, Mombasa, Kenya, Auction Price, US cents per kg, From July 1998, Best Pekoe Fannings	0.3
PTIN	USD	Tin, standard grade, LME spot price, USD per metric ton	0.2
PURAN	USD	Uranium, NUEXCO, Restricted Price, Nuexco exchange spot, USD per pound	0.5
PWHEAMT	USD	Wheat, No.1 Hard Red Winter, ordinary protein, FOB Gulf of Mexico, USD per metric ton	1.7
PWOOLC	USD	Wool, coarse, 23 micron, Australian Wool Exchange spot quote, US cents per kilogram	0.3
PWOOLF	USD	Wool, fine, 19 micron, Australian Wool Exchange spot quote, US cents per kilogram	0.2
PZINC	USD	Zinc, high grade 98 percent pure, USD per metric ton	0.6

Table 3: Model Selection

	Number of global factors				
	$r=1$	$r=2$	$r=3$	$r=4$	$r=5$
IC^*	11.77	11.92	12.07	12.26	12.41
$log(V)$	11.57	11.53	11.48	11.47	11.43

Table 4: Variance decomposition of commodity indices

Indices	***Global***	***Non Fuel***	***Food-Bev.***	***Food***	***Bev.***	***Ind. Inputs***	***Agric. Raw Mat.***	***Metals***	***Fuel***	***Oil***	***Idiosyncratic***
All Commodities	34.1	0.2	0.1	0	0	0	0	0.2	62.7	0	2.6
Non-Fuel	68.6	3.1	1.7	0.1	0.5	0	0.8	3.7	0	0	21.3
Food and Beverages	58.0	0	6.7	0.4	1.8	0	0	0	0	0	33.2
Food	55.4	0.1	8.6	0.4	0	0	0	0	0	0	35.6
Beverages	9.3	1.0	1.0	0	50.4	0	0	0	0	0	38.4
Industrial Inputs	48.4	7.9	0	0	0	0.7	2.0	9.2	0	0	31.8
Agricultural Raw Materials	10.5	1.4	0	0	0	31.2	8.3	0	0	0	48.6
Metals	43.2	7.5	0	0	0	5.2	0	13.8	0	0	30.3
Energy	19.9	0	0	0	0	0	0	0	78.1	0	2.0
Oil	17.7	0	0	0	0	0	0	0	81.2	0	1.1

Note: The table reports the model-based variance decomposition of commodity indices estimated over the sample January 1981 - December 2015.

Table 5: Variance decomposition of commodity prices

Commodity prices	*Global*	*Non-Fuel*	*Food-Bev.*	*Food*	*Bev.*	*Ind. Inputs*	*Agric. Raw Mat.*	*Metals*	*Fuel*	*Oil*	*Idiosyncratic*
Aluminium	23.6	7.4	-	-	-	3.4	-	0.5	-	-	65.1
Bananas	0.4	0.3	1	1.2	-	-	-	-	-	-	96.9
Barley	21.6	0.1	8	0.01	-	-	-	-	-	-	70.0
Beef	0.8	1	0.5	0.4	-	-	-	-	-	-	97.7
Coal	16.7	-	-	-	-	-	-	-	0.5	-	82.8
Cocoa	4.4	0.3	2.4	-	4.0	-	-	-	-	-	88.9
Coffee Arabica	5.2	0.7	0.1	-	67.3	-	-	-	-	-	26.7
Coffee Robusta	6.4	0.5	0.1	-	70.1	-	-	-	-	-	22.9
Rapeseed Oil	15.2	0.2	0.01	0.04	-	-	-	-	-	-	84.5
Copper	30.8	9.4	-	-	-	1.4	-	6.2	-	-	52.2
Cotton	13.7	0.4	-	-	-	0.2	2.1	-	-	-	83.6
Fish meal	4.3	1	4.1	2.7	-	-	-	-	-	-	87.9
Peanuts	1.1	0.8	20.3	8.0	-	-	-	-	-	-	69.8
Hides	3.7	0.6	-	-	-	15.2	32.2	-	-	-	48.3
Iron ore	2.6	11.1	-	-	-	3.3	-	77.0	-	-	6.0
Lamb	6.7	1.1	9.3	0.2	-	-	-	-	-	-	82.7
Lead	18.9	3.9	-	-	-	1.3	-	1.7	-	-	74.3
Soft logs	1.1	0	-	-	-	3.3	1.1	-	-	-	94.2
Hard logs	0.7	0	-	-	-	54.1	4.3	-	-	-	40.9
Maize	23.0	0.9	21	0.4	-	-	-	-	-	-	55.0
EU Natural gas	0.0	-	-	-	-	-	-	-	5.7	-	94.3
JP Natural gas	1.3	-	-	-	-	-	-	-	0.4	-	98.3
US Natural gas	1.6	-	-	-	-	-	-	-	1.0	-	97.4
Nickel	19.2	10.1	-	-	-	1.8	-	0.8	-	-	68.1
Brent oil	17.0	-	-	-	-	-	-	-	78.1	0.4	4.5
Dubai oil	17.6	-	-	-	-	-	-	-	77.0	2.0	3.3
WTI oil	16.1	-	-	-	-	-	-	-	77.2	5	1.3
Olive oil	2.7	2.8	10.1	0.4	-	-	-	-	-	-	84.0
Oranges	0.6	0	1	0.8	-	-	-	-	-	-	97.6
Palm oil	28.7	0.3	2.3	0.05	-	-	-	-	-	-	68.6
Pork	0.4	0.01	0.2	0.0	-	-	-	-	-	-	99.4
Poultry	0.0	1	3	0.9	-	-	-	-	-	-	95.8
Rice	2.7	1.6	3.4	0.02	-	-	-	-	-	-	92.4
Rubber	22.1	2.8	-	-	-	0.01	0.7	-	-	-	74.4
Salmon	6.0	1.5	2.8	0.06	-	-	-	-	-	-	89.7
Hard Sawnwood	2.7	0.1	-	-	-	47.1	3.4	-	-	-	46.7
Soft Sawnwood	0.0	0.0	-	-	-	3.1	0.9	-	-	-	96.0
Shrimp	0.4	0.0	0.1	23.8	-	-	-	-	-	-	75.8
Soybean meal	28.6	0.3	38	0.1	-	-	-	-	-	-	33.2
Soybean oil	45.9	1.0	13	0.0	-	-	-	-	-	-	39.6
Soybeans	48.7	0.8	38	0.2	-	-	-	-	-	-	12.2
EU sugar	10.1	2.7	8.4	0.2	-	-	-	-	-	-	78.5
Sugar	4.6	0.0	1	0.9	-	-	-	-	-	-	93.8
US sugar	3.1	0	0.8	1.3	-	-	-	-	-	-	94.8
Sunflower oil	40.1	43	9.9	0.1	-	-	-	-	-	-	6.5
Tea	0.9	0.4	0.3	-	1	-	-	-	-	-	97.6
Tin	21.9	2.0	-	-	-	0.4	-	2.0	-	-	73.7
Uranium	1.8	0.0	-	-	-	0.01	-	1.1	-	-	97.1
Wheat	17.1	0.2	10.1	0.5	-	-	-	-	-	-	72.0
Coarse wool	13.0	4.1	-	-	-	1.0	2.1	-	-	-	79.9
Fine wool	10.4	3	-	-	-	0.0	4.7	-	-	-	81.9
Zinc	18.6	10.7	-	-	-	3.1	-	3.0	-	-	64.6

Note: The table reports the model-based variance decomposition of commodity prices estimated over the sample January 1981 - December 2015.

Table 6: Out-of-sample forecasting performance

	h=1			*h=12*		
	RMSE	***Relative MSE***		***RMSE***	***Relative MSE***	
Indices	***Benchmark***	***r=1***	***r=2***	***Benchmark***	***r=1***	***r=2***
All commodities	5.22	0.84*	0.85*	24.98	1.05	1.06
Non-fuel	3.06	0.82**	0.84*	15.21	1.11	1.11
Food and Beverages	3.19	0.85**	0.85**	14.27	1.09**	1.09**
Food	3.30	0.85**	0.85**	14.64	1.11***	1.11***
Beverages	4.19	0.97	0.96	17.67	1.04	1.04
Industrial Inputs	3.92	0.83**	0.86	20.65	1.01	1.01
Agricultural Raw Materials	3.12	0.81**	0.81**	14.71	0.98*	0.98
Metals	5.05	0.88	0.95	26.15	1.04	1.04
Energy	7.33	0.88	0.89	32.57	1.05	1.05
Oil	8.55	0.88	0.89	35.68	1.01	1.01

Note: The table shows the root mean forecast error (RMSE) of a benchmark model, i.e. a constant growth model and the MSE of the candidate forecasting model relative to the benchmark. A ratio smaller than 1 indicates that the factor model forecasts are on average more accurate. (*), (**) and (***) indicate rejection of the null of equal predictive accuracy at the 10%, 5% and 1% level based on the Diebold and Mariano (1995) statistic. The model estimation is rolling using a fixed window of 20 years and the estimation starts in 2001:1. The evaluation period goes from 2001:2 to 2015:12. As robustness check, the table also displays the relative MSE for a model specification with two global factors.

Table 7: Out-of-sample forecasting performance

	h=1			*h=12*		
Commodity prices	***RMSE Benchmark***	***Relative MSE r=1***	***r=2***	***RMSE Benchmark***	***Relative MSE r=1***	***r=2***
Aluminium	5.14	0.89	0.88	22.10	1.03	1.03
Bananas	11.61	0.99	1.00	22.69	1.00	1.00
Barley	6.49	0.89 *	0.90	27.69	1.01	1.01
Beef	4.52	0.94 *	0.94 *	16.08	1.00	1.00
Coal	7.06	0.85 *	0.85 *	37.41	1.02	1.02
Cocoa	6.05	0.98	0.98	23.34	1.04	1.04
Coffee Arabica	6.51	0.99	0.99	28.24	0.98	0.98
Coffee Robusta	5.91	0.98	0.98	26.51	0.97**	0.97**
Rapeseed Oil	5.75	0.84 **	0.85 **	27.12	0.98	0.98
Copper	7.05	0.82 *	0.81 *	32.63	1.05	1.05
Cotton	6.32	0.83 **	0.83 **	32.30	0.98 *	0.98 *
Fish meal	4.88	0.88 ***	0.87 ***	22.02	1.04	1.05
Peanuts	4.91	1.09	1.10	27.16	1.06	1.06
Hides	6.87	0.94	0.95	25.77	1.04	1.04
Iron ore	8.77	1.88 ***	3.78 ***	35.50	3.12 ***	3.12 ***
Lamb	3.44	0.88 **	0.87 **	17.87	1.00	1.00
Lead	7.99	0.96	0.96	36.88	1.03	1.03
Soft logs	6.64	0.86 **	0.86 **	13.24	1.02	1.02
Hard logs	3.15	0.88 ***	0.88 ***	14.86	1.00	1.00
Maize	6.30	0.96	0.97	27.03	1.02	1.03
EU Natural gas	6.41	1.26	1.38 **	34.63	1.44	1.47
JP Natural gas	7.13	0.98	0.98	29.33	1.00	1.00
US Natural gas	13.22	1.00	1.00	44.65	1.01	1.01
Nickel	8.99	0.92	0.91	42.67	1.05	1.05
Brent oil	8.97	0.90	0.91	36.18	1.00	1.01
Dubai oil	8.48	0.87	0.88	35.38	1.01	1.01
WTI oil	8.78	0.89	0.90	36.07	1.01	1.02
Olive oil	4.19	0.90 **	0.90 **	18.33	1.03	1.03
Oranges	12.05	0.96	0.97	23.08	1.13 ***	1.13 ***
Palm oil	7.83	0.92	0.92	32.21	1.04	1.04
Pork	9.14	0.98	0.98	23.38	0.99	0.99
Poultry	1.27	0.54 ***	0.54 ***	6.32	0.96	0.96
Rice	5.92	0.81	0.81	25.86	1.01	1.01
Rubber	8.27	0.89 *	0.90 *	37.20	1.00	1.00
Salmon	7.03	0.92	0.93	22.26	1.04	1.04
Hard Sawnwood	2.12	0.99	1.00	8.13	1.05**	1.05 *
Soft Sawnwood	5.72	0.91	0.91	10.04	0.96**	0.96 **
Shrimp	5.00	0.98	0.99	20.98	1.00	1.00
Soybean meal	7.10	0.93	0.92 *	25.04	1.05	1.05
Soybean oil	6.06	0.91	0.91	27.67	1.02	1.02
Soybeans	6.51	0.91 *	0.90 *	26.61	1.03	1.03
EU sugar	2.15	0.86	0.86 *	9.67	1.06*	1.06 *
Sugar	7.71	0.97	0.97	30.31	1.04	1.04
US sugar	3.53	0.88 **	0.88 **	17.71	0.97	0.97
Sunflower oil	9.31	0.88	0.88	38.76	1.19	1.19
Tea	7.08	0.99	0.99	19.23	1.05	1.05
Tin	6.73	0.88**	0.88 **	33.83	1.00	1.00
Uranium	6.55	0.90	0.90	38.87	0.98	0.98
Wheat	7.41	0.96	0.96	29.83	1.05**	1.05 *
Coarse wool	5.80	0.91*	0.91 *	28.39	1.03	1.03
Fine wool	6.06	0.91**	0.91 **	25.82	1.04	1.04
Zinc	6.84	0.92	0.92	36.65	1.01	1.01

Note: The table shows the root mean forecast error (RMSE) of a benchmark model, i.e. a constant growth model and the MSE of the candidate forecasting model relative to the benchmark. A ratio smaller than 1 indicates that the factor model forecasts are on average more accurate. (*), (**) and (***) indicate rejection of the null of equal predictive accuracy at the 10%, 5% and 1% level based on the Diebold and Mariano (1995) statistic. The model estimation is rolling using a fixed window of 20 years and the estimation starts in 2001:1. The evaluation period goes from 2001:2 to 2015:12. As robustness check, the table also displays the relative MSE for a model specification with two global factors.