Common Factors of Commodity Prices[1]

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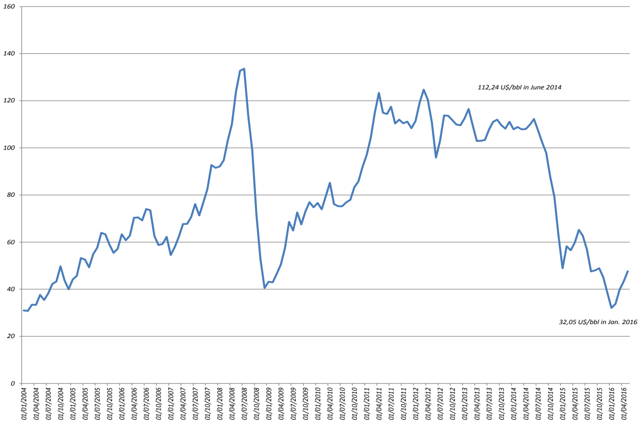
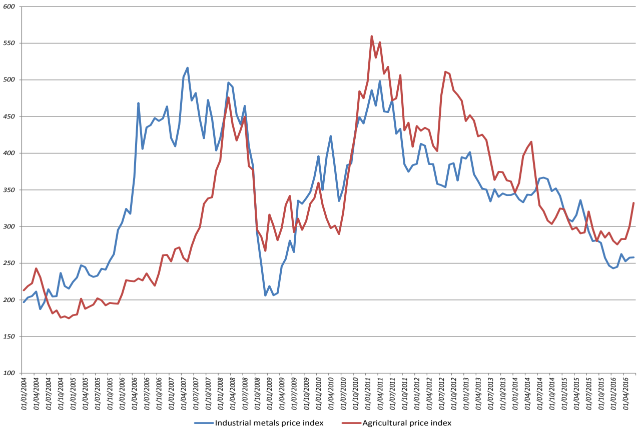
[1] The views expressed here are those of the authors and do not necessarily reflect those of the Banque de France, the ECB or the Eurosystem, the Federal Reverse Bank of New York or the Federal Reserve System.

Large drop in oil prices since mid-2014: How to explain?



Common pattern in commodities: Can we use it?



Motivations

- High level of co-movement among a broad group of commodity prices since the beginning of the 2000s.
- The observed commonality suggests that a few common forces could drive the bulk of commodity price fluctuations.
- Global demand shocks have been identified as a common source of price variation (Barsky and Kilian (2002), Aastveit et al. (2014), Alquist and Coibion (2014)).
- Disentagling the underlying sources of fluctuations is important to assess the impact and design the appropriate policy responses (Kilian (2009)).

What do we do in this paper?

Main idea: to understand oil prices, let's look at other commodities

- Studies the co-movement in commodity prices.
- Estimates latent factors from a large-cross section of commodity prices.
- Distinguishes between **common (global) and local (block) factors**:
  - Global factors affect *most or all* commodity prices (pervasive shocks).
  - Block factors are confined to a small group of commodities belonging to the same category and generate limited comovement (non-pervasive shocks).
- Studies the predictive accuracy of the model in a (real-time) out-of-sample forecasting exercise.

Why using block factors?

- Introduction of local factors to model cross-correlation among idiosyncratic components:
  - Improving efficiency.
  - Economic interpretation: **different shocks are likely to produce distinct consequences on the cross-correlation of commodity prices**.
    - Shocks related to changes in global real activity are likely to generate positive correlation among prices.
    - Supply shocks or demand-specific shocks are unlikely to represent common sources of movement since they have a more limited propagation across markets.

Main results

- We find that there is a **single global factor** that captures the bulk of commodity price fluctuations (70% of the variance of non-fuel commodities; 20% of the price of oil).
- The factor loadings associated with the global factor are positive and the global factor seems to follow closely changes in global economic activity.
- A look at historical episodes of major commodity price changes also suggests that the **global factor seems to be associated with global demand shocks**.
- The global factor has predictive power for commodity prices and its predictability increased during the Great Recession.
- Interest for practitioners: Use in real-time to estimate demand component in the evolution of many commodities

Related literature

- Factor models with a block structure (e.g. Kose et al (2003), Banbura et al (2010), Miranda Agrippino and Rey (2015)).
- Factor models fitted on commodity prices:
    - Forecasting commodity prices themselves or other macro and financial variables (e.g. West and Wang (2014), Poncela et al (2015), Gospodinov and NG (2013), Chen et al. (2012)).
    - Assessing the driving forces of the covariation (e.g. Byrne et al. (2012), Chen et al (2012), West and Wang (2014)). Alquist and Coibion (2015) use a structural macro model to identify a factor capturing changes in global demand conditions.
- Studying the sources of oil price variations: SVAR identified using sign restrictions (Kilian and Murphy (2015)). Groen, McNeil, Middeldorp (2013) and Bernanke (2016) look at the co-movement between commodity and equity prices to disentangle demand versus supply shocks.

Data

- Monthly commodity (spot) prices [n=52] from different categories, including both fuel and non-fuel commodities.
- Sample period goes from Jan1981 to July2015. Source: IMF primary commodity dataset.
- 10 price indices and sub-indices, representing the major commodity sectors, constructed as weighted averages of individual commodity prices (based on trade values):
  - all commodities, non fuel, food&beverages (further decomposed into food and beverages), industrial inputs (further decomposed into agricultural raw materials and metals), fuel and oil.
- Oil prices represent roughly 60 percent of the overall index of commodity prices.
- Prices are taken in differences of logs and standardized.

A dynamic factor model for commodity prices

- Let $\mathbf{x}_t$ be an $(n \times 1)$ vector of all commodity prices series where x_{it} denotes the price of commodity i at time t. We assume that $\mathbf{x}_t$ has a *factor representation*:

$$\mathbf{x}_t = \Lambda \mathbf{f}_t + \mathbf{e}_t.$$

- $\mathbf{f}_t$ is an $(r \times 1)$ vector of stationary processes with mean zero, Λ is an $(n \times r)$ matrix of factor loadings and the idiosyncratic components, $\mathbf{e}_t$, are uncorrelated with $\mathbf{f}_t$ at all leads and lags.
- The factors can be consistently estimated, as $n, T \to \infty$, when idiosyncratic components are weakly cross–sectionally correlated (see, e.g. Stock and Watson (2002)).
- This assumption can be violated if the data are characterized by a block structure.

Factor model with a block structure

- We explicitly model the local correlations by further decomposing:

$$\mathbf{x}_t = \Lambda_g \mathbf{f}_{g,t} + \Lambda_b \mathbf{f}_{b,t} + \mathbf{e}_t$$

- $\mathbf{f}_{g,t}$ is an $(r_g \times 1)$ vector of global factors and $\mathbf{f}_{b,t}$, $b = 1, ..., B$ are $(r_b \times 1)$ vectors of block-specific factors
- Λ_g and Λ_b are matrices of factor loadings
- $\mathbf{e}_t$ is an n-dimensional vector of idiosyncratic terms.
- **Total number of estimated factors**: $r = (r_g + r_b \times B)$.

Factor dynamics

- The factors follow a VAR(p) representation while the idiosyncratics are AR(1) processes.

$$\mathbf{f}_t = \Phi_1 \mathbf{f}_{t-1} + \Phi_2 \mathbf{f}_{t-2} ... + \Phi_p \mathbf{f}_{t-p} + \mathbf{u}_t, \mathbf{u}_t \sim iidN\left(\mathbf{0}, \Sigma_f\right)$$

$$\mathbf{e}_t = \Psi \mathbf{e}_{t-1} + \varepsilon_t, \varepsilon_t \sim N(0, \Sigma_e)$$

where $\mathbf{f}_t = \left[\begin{array}{cc} \mathbf{f}'_{g,t} & \mathbf{f}'_{b,t} \end{array}\right]$ and $\mathbf{u}_t = \left[\begin{array}{cc} \mathbf{u}'_{g,t} & \mathbf{u}'_{b,t} \end{array}\right]$

Identification of block factors

- Block factors are estimated by imposing zero restrictions on the factor representation.
- The identification of block factors requires Λ and Σ_f being block diagonal matrices.
- To keep the model parsimonious, we further assume that local factors are uncorrelated.

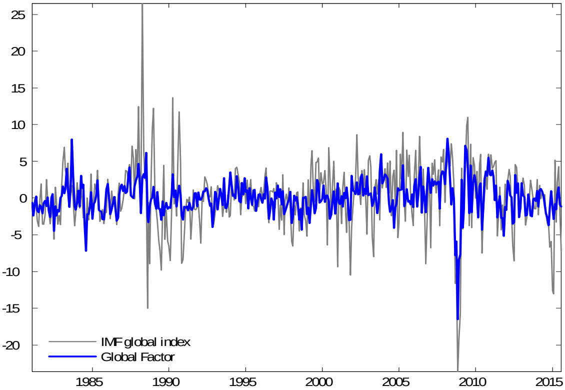
Model estimation

- The model is estimated using maximum likelihood:
  - ML is a consistent estimator under misspecification of the factor structure and computationally feasible for large N (Doz, Giannone and Reichlin (2006))
  - deals with missing data (Banbura and Modugno (2014)).
- This requires casting the DFM in state-space form and maximizing the likelihood using the EM algorithm (see, e.g. Dempster et al (1977), Watson and Engle (1983) and Sargent and Quah (1992))
- The EM algorithm requires only one run of the Kalman smoother at each iteration (computational complexity depends on the number of states $= r$)
- Principal component (PCs) estimates of the factors are used to initialize the algorithm.

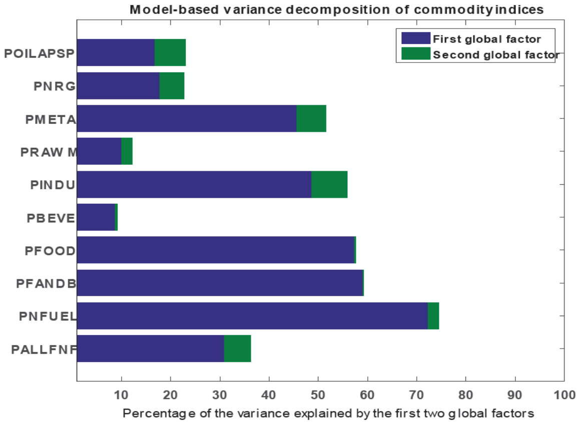
How many factors and blocks?

- We determine the optimal number of global factors:
  - Information Criterion as in Bai and Ng (2002) applied to the ML estimator;
  - Variance explained by the first r_G factors.
  - These suggest the presence of one single global factor.
- We determine the number of blocks to include in the model by following the structure of our database $(B = 9$ and $r_b = 1)$.
- Robustness checks:
  - Factor loadings associated with the first global factor are remarkably robust to alternative specifications of the block structure.

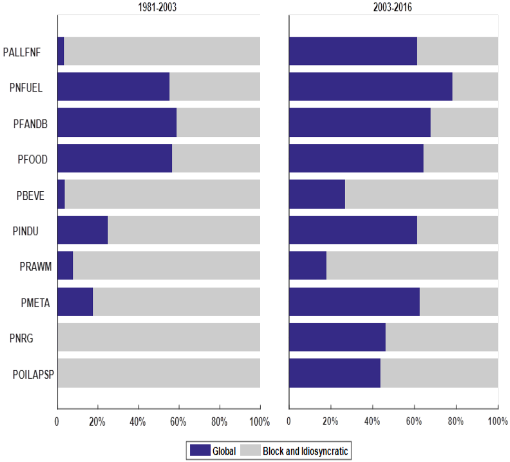
Global factor and IMF global index



Variance explained by global factors

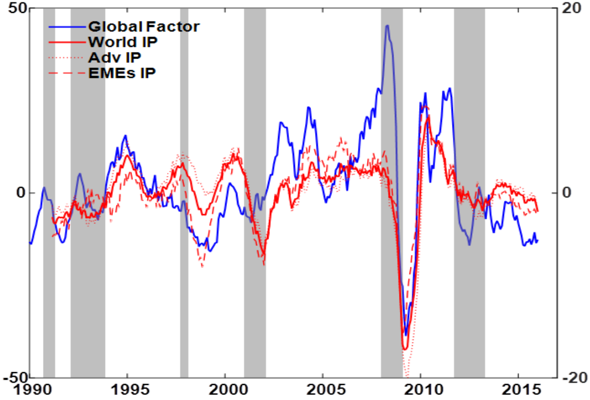


Reinforced comovement since beginning of 2000s



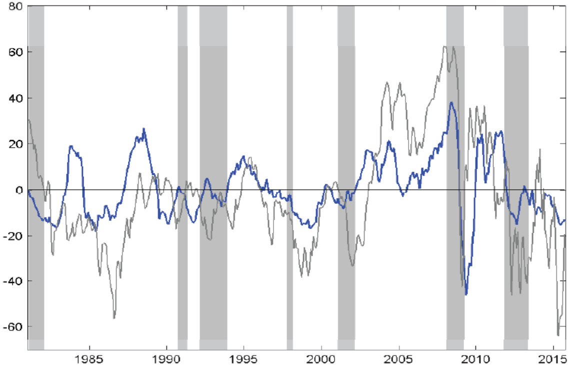
What does the global factor capture ?

Global factor correlates with measures of real economic activity (World IPI)



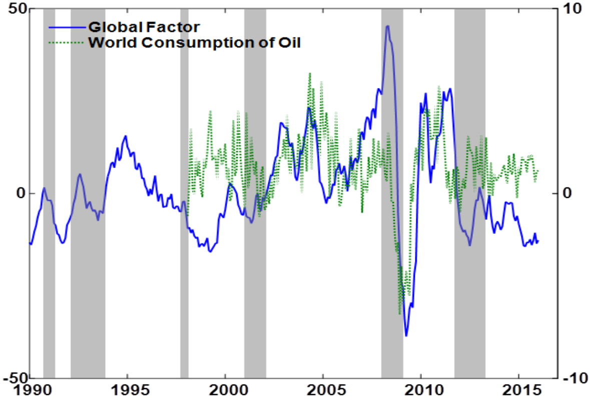
What does the global factor capture ?

Global factor correlates with measures of real economic activity (Kilian's index)

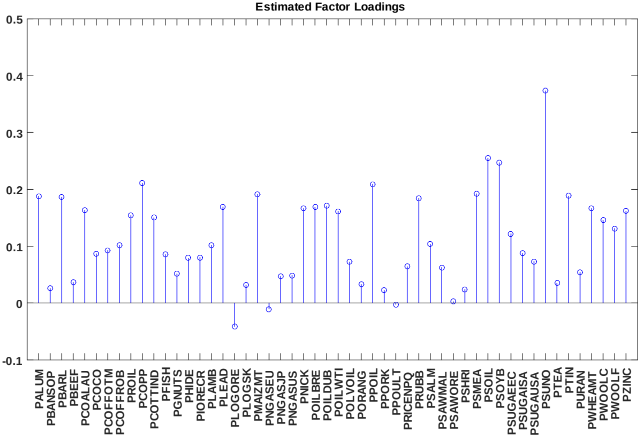


What does the global factor capture ?

Global factor and measures of oil consumption

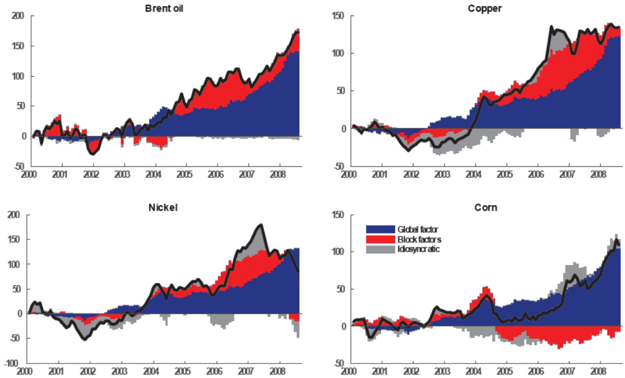


Commodities load positively to the global factor



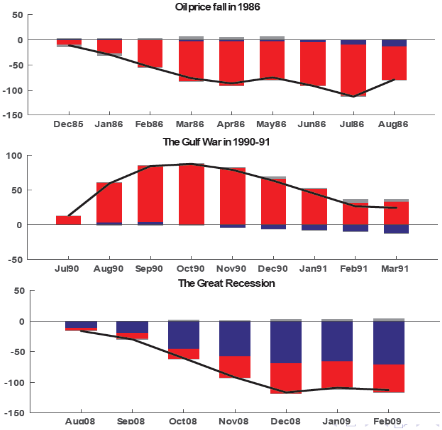
Factor-based decomposition of commodities in the 2000s

- Global factor explains a larger fraction of commodity price changes in a period typically associated with global demand shocks (EME+ADV countries

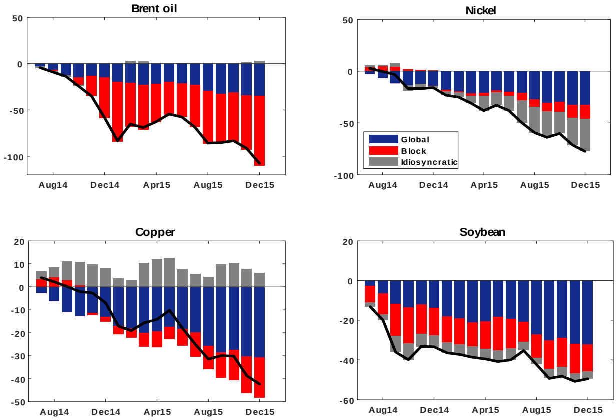


Factor-based decomposition of oil prices of 3 events

- An oil counter-shock, an oil shock and the Great Recession: fuel-specific factor and global factor cumulated contributions



What drives the recent commodity price fall since mid-2014?



Forecasting performance

- We finally study if the global factor has predictive power for commodity prices and indices.
- We run a real-time forecasting exercise using a rolling estimation window. Evaluation sample: 2001M2 to 2015M7.
- Forecasts of commodity indices are computed as weighted averages of commodity price forecasts.
- We compute both the average forecast error loss difference between the model and the benchmark (i.e. constant growth model) over the entire evaluation sample and rolling average losses as in Giacomini and Rossi (2010).

Forecasting results

- Evidence of predictive power at short-term horizons

Out-of-Sample forecasting results - commodity indices

	h=1					h=12				
	RMSE	Relative MSE				RMSE	Relative MSE			
Indices	Benchmark	rG=1		rG=2		Benchmark	rG=1		rG=2	
All commodities	5.18	0.84	*	0.85		23.86	1.08		1.08	
Non Fuel	3.04	0.82	**	0.83	**	14.85	1.12		1.13	
Food and Beverages	3.12	0.85	**	0.85	**	14.01	1.10	***	1.10	***
Food	3.23	0.85	**	0.85	**	14.34	1.12	***	1.13	***
Beverages	4.24	0.97		0.97		17.89	1.04		1.03	
Industrial inputs	3.94	0.83	**	0.83	**	20.32	1.02		1.02	
Agricultural raw materials	3.13	0.81	**	0.81	*	14.52	0.99	*	0.99	
Metals	5.07	0.88		0.88		25.78	1.04		1.04	
Fuel	7.28	0.88		0.89		31.69	1.02		1.03	
Oil	8.44	0.88		0.89		33.93	1.03		1.05	

The table reports the root mean forecast error (RMSE) of a constant growth model (benchmark) and the MSE of the factor model relative to the benchmark. (*), (**) and (***) indicate rejection of the null of equal predictive accuracy at the 10%, 5% and 1% level based on the Diebold and Mariano's (1995) statistic. Evaluation period: 2001:2 to 2015:7

Conclusions

- We find that the bulk of the fluctuations in commodity prices is well summarized by a single global factor.
- The global factor is pervasive, loads positively commodity prices and co-moves with measures of global real economic activity.
- The inspection of historical episodes of major commodity price changes suggests that the factor is associated with global demand shocks.
- This factor explains about 30 percent of the oil price fall from July 2014 to December 2015 while it captures most of the fall in base metals.
- The real-time forecasting performance of the model confirms that the high level of commonality is a genuine feature of the data that survives in out-of-sample assessment.