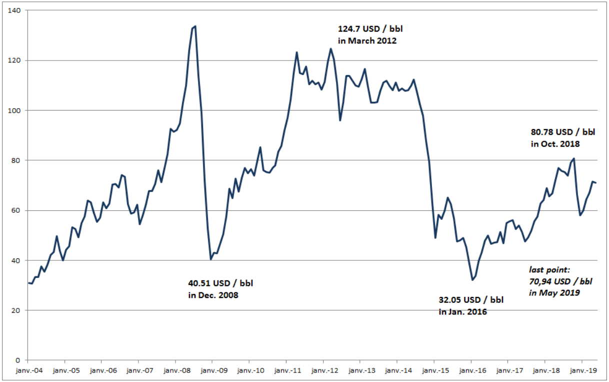
# Common Factors of Commodity Prices[1]

Simona Delle Chiaie (ECB)
Laurent Ferrara (Banque de France)
Domenico Giannone (FED New York & CEPR)

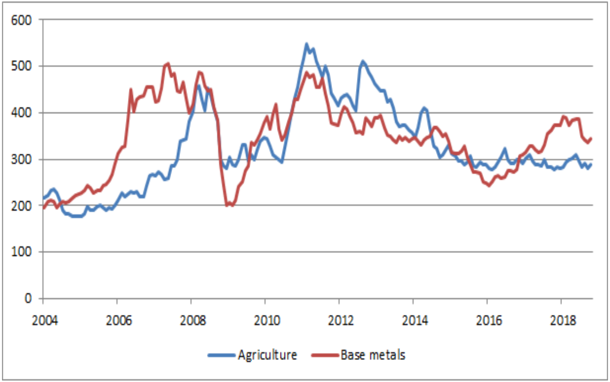
IJCB Annual Conference
Oslo, June 4, 2019

[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.

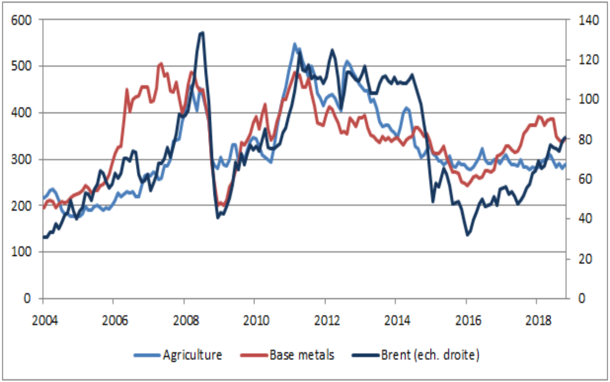
# Oil prices: How to explain the cyclical movements?



# Common pattern in commodities: Can we use it?



# 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.

# 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.

# 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)).

# 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

- Study the co-movement in commodity prices by estimating latent factors from a large-cross section of commodity prices.

# What do we do in this paper?

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

- Study the co-movement in commodity prices by estimating latent factors from a large-cross section of commodity prices.
- Distinguish 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).

# What do we do in this paper?

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

- Study the co-movement in commodity prices by estimating latent factors from a large-cross section of commodity prices.
- Distinguish 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).
- Show that the global factor can be considered as a proxy for global demand

# What do we do in this paper?

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

- Study the co-movement in commodity prices by estimating latent factors from a large-cross section of commodity prices.
- Distinguish 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).
- Show that the global factor can be considered as a proxy for global demand
- Real-time applications of the model: Forecasting and Identification of global demand contribution in commodity prices evolutions

# Why using block factors?

- Block components are a parsimonious way to account for cross-correlations among idiosyncratic components:
  - Weak identification in the presence of strong cross-sectional correlations

# Why using block factors?

- Block components are a parsimonious way to account for cross-correlations among idiosyncratic components:
  - Weak identification in the presence of strong cross-sectional correlations
- Shocks of different nature have different consequences for the cross-correlation between commodity prices:
  - Changes in global economic activity affects the demand of a broad group of commodities and move prices in the same direction
  - Market-specific shocks have a more limited propagation across markets generating only local correlation

# Why using block factors?

- Block components are a parsimonious way to account for cross-correlations among idiosyncratic components:
    - Weak identification in the presence of strong cross-sectional correlations
- Shocks of different nature have different consequences for the cross-correlation between commodity prices:
    - Changes in global economic activity affects the demand of a broad group of commodities and move prices in the same direction
    - Market-specific shocks have a more limited propagation across markets generating only local correlation
- A simple strategy for disentangling the sources of fluctuations in commodity prices

## Main results

- We find that there is a **single global factor** that captures the bulk of commodity price fluctuations

# Main results

- We find that there is a **single global factor** that captures the bulk of commodity price fluctuations
- The factor loadings associated with the global factor are all positive, meaning that the global factor has very limited effects on relative prices

# Main results

- We find that there is a **single global factor** that captures the bulk of commodity price fluctuations
- The factor loadings associated with the global factor are all positive, meaning that the global factor has very limited effects on relative prices
- Based on historical episodes of major commodity price changes, we argue that the **global factor seems to be associated with global demand shocks**

# Main results

- We find that there is a **single global factor** that captures the bulk of commodity price fluctuations
- The factor loadings associated with the global factor are all positive, meaning that the global factor has very limited effects on relative prices
- Based on historical episodes of major commodity price changes, we argue 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.

# Main results

- We find that there is a **single global factor** that captures the bulk of commodity price fluctuations
- The factor loadings associated with the global factor are all positive, meaning that the global factor has very limited effects on relative prices
- Based on historical episodes of major commodity price changes, we argue 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

1. Factor models with a block structure (e.g. Kose et al (2003), Banbura et al (2010), Miranda- Agrippino and Rey (2015)).

# Related literature

1. Factor models with a block structure (e.g. Kose et al (2003), Banbura et al (2010), Miranda- Agrippino and Rey (2015)).

2. Factor models fitted on commodity prices:
   - Forecasting commodity prices themselves or other macro and financial variables (e.g. West and Wong (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.

# Related literature

1. Factor models with a block structure (e.g. Kose et al (2003), Banbura et al (2010), Miranda- Agrippino and Rey (2015)).
2. Factor models fitted on commodity prices:
   - Forecasting commodity prices themselves or other macro and financial variables (e.g. West and Wong (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.
3. 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 DFM with blocks 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, $\Lambda$ 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
- $\Lambda_g$ and $\Lambda_b$ 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 $\mathbf{f}_t = \begin{bmatrix} \mathbf{f}'_{g,t} & \mathbf{f}'_{b,t} \end{bmatrix}$ and $\mathbf{u}_t = \begin{bmatrix} \mathbf{u}'_{g,t} & \mathbf{u}'_{b,t} \end{bmatrix}$

# Identification of block factors

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

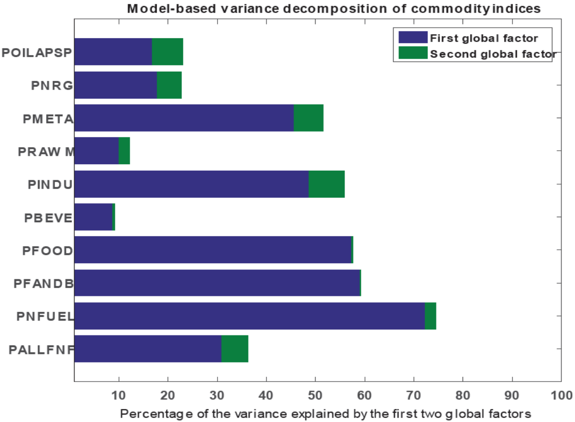
# Model estimation

- 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.

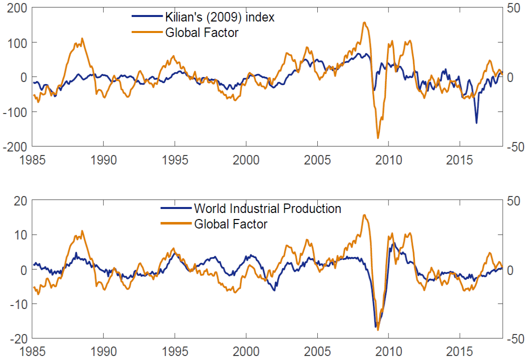
# How many factors and blocks?

- 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 $\left(B = 9 \text{ and } r_b = 1\right)$.
- Robustness checks:
  - Factor loadings associated with the first global factor are remarkably robust to alternative specifications of the block structure.

# Commodity prices fluctuations are captured by a single global factor

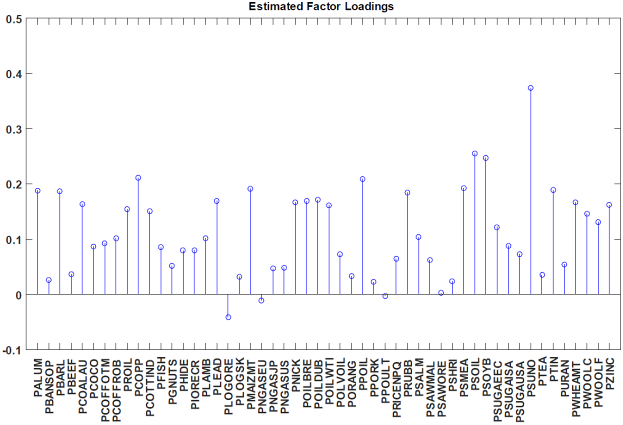


# The global factor is strongly related to global economy

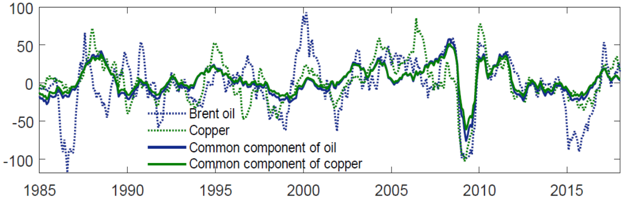


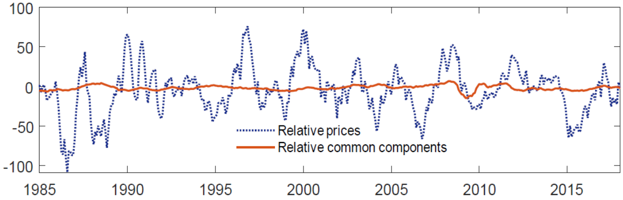

* All series are in annual growth rates. The World Industrial Production is given by the monthly industrial production for the OECD countries plus 6 other majour countries (Brazil, China, Indonesia, the Russian Federation and South Africa) as in Baumeister and Hamilton (2008).

# Commodities load positively to the global factor



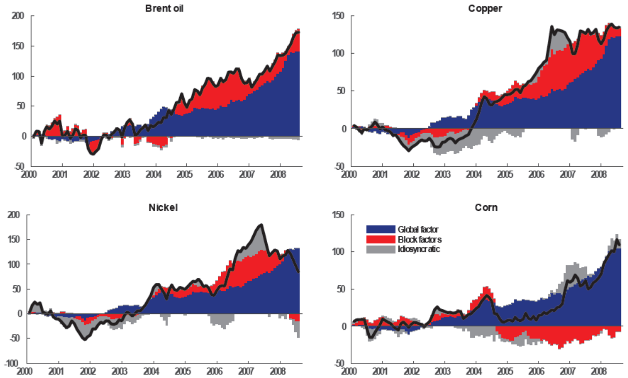
# The global factor has limited effects on relative prices



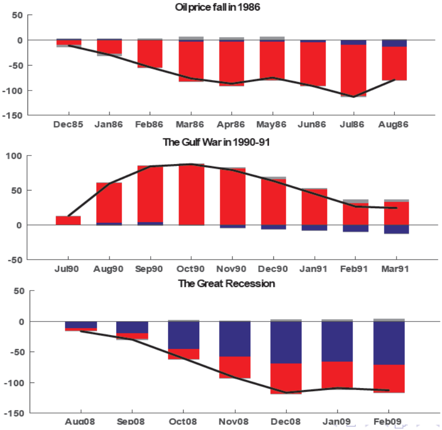
# Factor-based decomposition of commodities in the 2000s

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

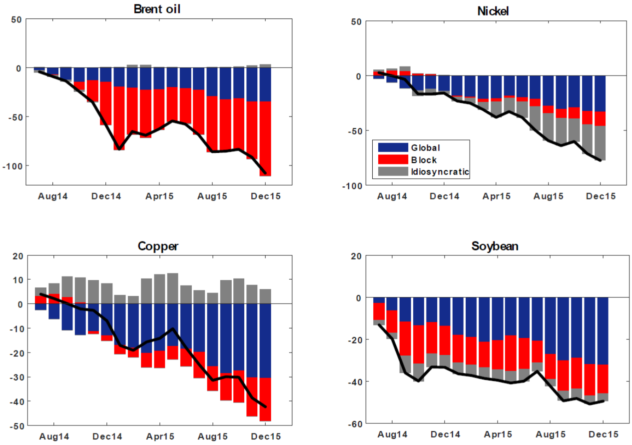


# Factor-based decomposition of oil prices of 3 events

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



# What has driven the commodity price fall in 2014-15?



# Real-time forecasting performance

- We 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

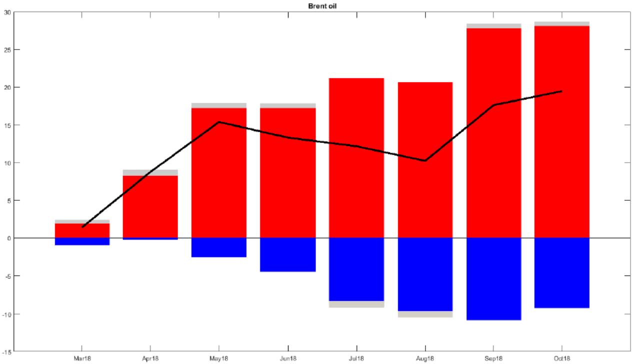
- Evidence of predictive power only at short-term horizons

Out-of-Sample forecasting results - commodity indices

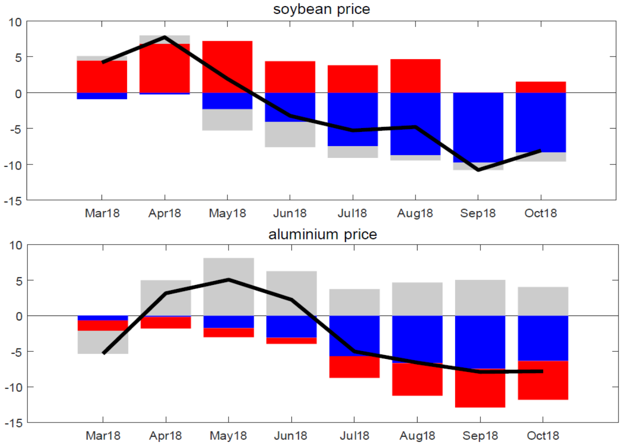
| | *h=1* | | | | | *h=12* | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *RMSE* | *Relative MSE* | | | | *RMSE* | *Relative MSE* | | | |
| Indices | *Benchmark* | *rG=1* | | *rG=2* | | *Benchmark* | *rG=1* | | *rG=2* | |
| **All commodities** | 5.18 | 0.84 | * | 0.85 | | 23.86 | 1.08 | | 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

# Real-time decomposition of cumulated oil prices between Feb. and Oct. 2018



# Hot topic: Effect of trade tariffs on commodity prices?



# Conclusions

- Looking at the comovement in a broad group of commodity prices is key to identify the nature of commodity price fluctuations

# Conclusions

- Looking at the comovement in a broad group of commodity prices is key to identify the nature of commodity price fluctuations
- We find that the bulk of the fluctuations in commodity prices is well summarized by a single global factor.

# Conclusions

- Looking at the comovement in a broad group of commodity prices is key to identify the nature of commodity price fluctuations
- We find that the bulk of the fluctuations in commodity prices is well summarized by a single global factor.
- The global factor has limited effects on relative prices and is closely related to measures of global economic activity.

# Conclusions

- Looking at the comovement in a broad group of commodity prices is key to identify the nature of commodity price fluctuations
- We find that the bulk of the fluctuations in commodity prices is well summarized by a single global factor.
- The global factor has limited effects on relative prices and is closely related to measures of global economic activity.
- Ex post narrative identification: The inspection of historical episodes of major commodity price changes suggests that the factor is associated with global demand shocks.

# Conclusions

- Looking at the comovement in a broad group of commodity prices is key to identify the nature of commodity price fluctuations
- We find that the bulk of the fluctuations in commodity prices is well summarized by a single global factor.
- The global factor has limited effects on relative prices and is closely related to measures of global economic activity.
- Ex post narrative identification: The inspection of historical episodes of major commodity price changes suggests that the factor is associated with global demand shocks.
- Real-time applications of the model for (i) forecasting and (ii) identification of global demand components in commodity prices