

Commodity Prices, Commodity Currencies, and Global Economic Developments

Jan J. J. Groen Paolo A. Pesenti

Federal Reserve Bank of New York

August 16-17, 2012

FGV-Vale Conference 'The Economics and Econometrics of Commodity
Prices', Rio de Janeiro

First...

The views expressed in the paper and this presentation are those of the authors and do not necessarily reflect the position of the Federal Reserve Bank of New York or the Federal Reserve System.

In case we need motivation...

... refer to Bernanke (June 2008 speech “Outstanding Issues in the Analysis of Inflation”).

- Emphasizes importance for policy:
 - Forecasting commodity price changes.
 - Understanding the factors that drive those changes.
- Spectacular commodity price swings in recent times:
 - Oil price more than doubled between the end of 2006 and the time of the Bernanke speech.
 - Food prices rose by about 50 percent over same time horizon.

At time of speech, inflationary pressures very much in the minds of monetary policymakers across the globe.

- Soon after: near-collapse of trade worldwide, plunge in commodity prices, disinflation risks.

In case we need motivation...

... refer to Bernanke (June 2008 speech “Outstanding Issues in the Analysis of Inflation”).

- Emphasizes importance for policy:
 - Forecasting commodity price changes.
 - Understanding the factors that drive those changes.
- Spectacular commodity price swings in recent times:
 - Oil price more than doubled between the end of 2006 and the time of the Bernanke speech.
 - Food prices rose by about 50 percent over same time horizon.

At time of speech, inflationary pressures very much in the minds of monetary policymakers across the globe.

- Soon after: near-collapse of trade worldwide, plunge in commodity prices, disinflation risks.

In case we need motivation...

... refer to Bernanke (June 2008 speech “Outstanding Issues in the Analysis of Inflation”).

- Emphasizes importance for policy:
 - Forecasting commodity price changes.
 - Understanding the factors that drive those changes.
- Spectacular commodity price swings in recent times:
 - Oil price more than doubled between the end of 2006 and the time of the Bernanke speech.
 - Food prices rose by about 50 percent over same time horizon.

At time of speech, inflationary pressures very much in the minds of monetary policymakers across the globe.

- Soon after: near-collapse of trade worldwide, plunge in commodity prices, disinflation risks.

Commodity Price Forecasting: Policy Practice

- Central Banks: Produce forecasts for, e.g., future WTI oil spot prices and the IMF Non-Fuel Commodity Price Index.
- Based on futures prices, assuming that:
 - Futures prices efficiently incorporates public information.
 - Contains information about the global economy, not just individual commodity.
- Forecast model:

$$\Delta p_{t+h,t} = \alpha^h + (fp_t^h - p_t) + \epsilon_{t+h,t}, \quad t = 1, \dots, T$$

with $p_t = \ln(P_t)$ and P_t is a commodity spot price index, fp_t^h is log futures price for h -period horizon, and

$\Delta p_{t+h,t} = p_{t+h} - p_t$ for the forecasting horizon $h > 0$.

- **BUT:** Futures prices are biased predictors, especially since 2006.

Commodity Price Forecasting: Policy Practice

- Central Banks: Produce forecasts for, e.g., future WTI oil spot prices and the IMF Non-Fuel Commodity Price Index.
- Based on futures prices, assuming that:
 - Futures prices efficiently incorporates public information.
 - Contains information about the global economy, not just individual commodity.
- Forecast model:

$$\Delta p_{t+h,t} = \alpha^h + (fp_t^h - p_t) + \epsilon_{t+h,t}, \quad t = 1, \dots, T$$

with $p_t = \ln(P_t)$ and P_t is a commodity spot price index, fp_t^h is log futures price for h -period horizon, and

$\Delta p_{t+h,t} = p_{t+h} - p_t$ for the forecasting horizon $h > 0$.

- **BUT:** Futures prices are biased predictors, especially since 2006.

Commodity Price Forecasting: Policy Practice

- Central Banks: Produce forecasts for, e.g., future WTI oil spot prices and the IMF Non-Fuel Commodity Price Index.
- Based on futures prices, assuming that:
 - Futures prices efficiently incorporates public information.
 - Contains information about the global economy, not just individual commodity.
- Forecast model:

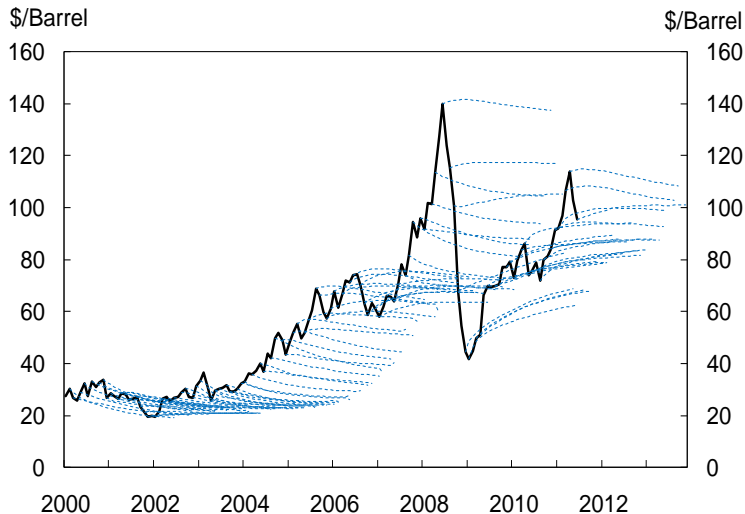
$$\Delta p_{t+h,t} = \alpha^h + (fp_t^h - p_t) + \epsilon_{t+h,t}, \quad t = 1, \dots, T$$

with $p_t = \ln(P_t)$ and P_t is a commodity spot price index, fp_t^h is log futures price for h -period horizon, and

$\Delta p_{t+h,t} = p_{t+h} - p_t$ for the forecasting horizon $h > 0$.

- **BUT:** Futures prices are biased predictors, especially since 2006.

WTI Futures vs. Realized Spots



Source: Bloomberg

Note: Dashed lines represent futures curves



Have we now reached some pragmatic consensus on how to predict swings in commodity prices?

Our paper: check to exactly how close we have come to that

It:

Have we now reached some pragmatic consensus on how to predict swings in commodity prices?

Our paper: check to exactly how close we have come to that

It:

- Conducts a horse race between various approaches to predict 10 different indices of commodity spot prices.
- Uses common factor models with global economic data and Rogoff-type currency-based models
- Attempts to beat simple statistical benchmarks, i.e, random walk and autoregressive processes.
- Basic message: inconclusiveness. Not necessarily pessimistic, but throws cold water on excessive hopes.

Have we now reached some pragmatic consensus on how to predict swings in commodity prices?

Our paper: check to exactly how close we have come to that

It:

- Conducts a horse race between various approaches to predict 10 different indices of commodity spot prices.
- Uses common factor models with global economic data and Rogoff-type currency-based models
- Attempts to beat simple statistical benchmarks, i.e, random walk and autoregressive processes.
- **Basic message: inconclusiveness. Not necessarily pessimistic, but throws cold water on excessive hopes.**

Three Approaches to Forecasting Commodity Prices

- **Atheist:** at the end of the day, nothing works. Just use random walk or autoregressive processes.
- **True Believer:** you need a theory, you need a model. The truth is out there, maybe fundamentals, maybe not. Squeeze data for information. In practice, use futures prices. Or commodity currencies.
- **Agnostic:** the rest of us. Open-mindedness and willingness to experiment. We'd love to be true believers, but not convinced yet.

Atheist Approach

There is nothing beyond the time series itself.

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

Atheist Approach

There is nothing beyond the time series itself.

- Use an *autoregressive (AR) model* as forecasting benchmark

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

with $\Delta p_{t-i+1,t-i} = p_{t-i+1} - p_{t-i}$ for $i = 1, \dots, k$.

k selected by sequentially applying BIC criterion.

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

Atheist Approach

There is nothing beyond the time series itself.

- Use an *autoregressive (AR) model* as forecasting benchmark

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

with $\Delta p_{t-i+1,t-i} = p_{t-i+1} - p_{t-i}$ for $i = 1, \dots, k$.

k selected by sequentially applying BIC criterion.

- The unconditional mean benchmark is simply:

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

implies a *random walk (RW) forecast* for p_t .

True Believers Approach

Three 'schools of thought':

- Commodity markets have relatively inelastic demand → small revisions in the expected future supply expansion can have large and highly volatile price effects.

True Believers Approach

Three 'schools of thought':

- Speculative strategies that drive commodity futures prices up must be reflected in higher spot prices today regardless of long-term fundamentals. Especially when there are rapid declines in short-term interest rates → opportunity cost of physical commodity holding is relatively low (Frankel, 2008).

True Believers Approach

Three 'schools of thought':

- Commodities typically represent significant components of output for most commodity exporting countries, and these countries are too small to have an impact on world markets. Their exchange rates thus move today anticipating future terms of trade adjustment; see Chen, Rogoff and Rossi (2010) - CRR hereafter.

•

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

$\Delta e_t^1, \dots, \Delta e_t^M$ are relative changes in U.S. dollar exchange rates of M commodity-exporting economies.

True Believers Approach

Three 'schools of thought':

- Commodities typically represent significant components of output for most commodity exporting countries, and these countries are too small to have an impact on world markets. Their exchange rates thus move today anticipating future terms of trade adjustment; see Chen, Rogoff and Rossi (2010) - CRR hereafter.

-

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

$\Delta e_t^1, \dots, \Delta e_t^M$ are relative changes in U.S. dollar exchange rates of M commodity-exporting economies.

True Believers Approach

Three 'schools of thought':

- Commodities typically represent significant components of output for most commodity exporting countries, and these countries are too small to have an impact on world markets. Their exchange rates thus move today anticipating future terms of trade adjustment; see Chen, Rogoff and Rossi (2010) - CRR hereafter.

-

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

M commodity-exporting economies: Australia, Canada, Chile, New Zealand, and South Africa.

Agnostic Approach

Use a large amount of information on global economic conditions, i.e., commodity exchange rates as well as...

- N macro-economic time series across major developed and developing countries: industrial production, business and consumer confidence data, retail sales volumes, unemployment rates, core consumer prices (excluding food and energy), money aggregates and interest rates.
- Data on inventories and production of industrial metals, oil, natural gas and coal.
- Baltic Dry Index (BDI) - aggregates shipping rates across many different routes and vessels.

Agnostic Approach

Use a large amount of information on global economic conditions, i.e., commodity exchange rates as well as...

- N macro-economic time series across major developed and developing countries: industrial production, business and consumer confidence data, retail sales volumes, unemployment rates, core consumer prices (excluding food and energy), money aggregates and interest rates.
- Data on inventories and production of industrial metals, oil, natural gas and coal.
- Baltic Dry Index (BDI) - aggregates shipping rates across many different routes and vessels.

Agnostic Approach

Use a large amount of information on global economic conditions, i.e., commodity exchange rates as well as...

- N macro-economic time series across major developed and developing countries: industrial production, business and consumer confidence data, retail sales volumes, unemployment rates, core consumer prices (excluding food and energy), money aggregates and interest rates.
- Data on inventories and production of industrial metals, oil, natural gas and coal.
- Baltic Dry Index (BDI) - aggregates shipping rates across many different routes and vessels.

Agnostic Approach

Use these data in **factor-augmented** regressions:

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

$f_{1,t}, \dots, f_{r,t}$: dynamic factors from large data set

Factor-Based Macro Forecasting Tools

- $y_t = \alpha'(x_{1,t} \cdots x_{N,t})' + \epsilon_t$; $t = 1, \dots, T$
with $x_{1,t}, \dots, x_{N,t}$ normalized and N large.
- Stock-Watson (2002) PC regression:
 $x_t = (x_{1,t} \cdots x_{N,t})' = \Lambda' F_t + e_t$ with F_t are combinations of x -variables using the r dominant eigenvectors from $X'X$ with $X = (x_1 \cdots x_T)'$
- Groen-Kapetanios (2009a) PLS regression: factors f_t are orthogonal combinations of x -variables using r^* dominant eigenvectors from $X'yy'X$ with $y = (y_1 \cdots y_T)$
- Note $r^* \leq r$ and $f_t \subseteq F_t$. PLS regression directly selects that subset from F_t that has the best (in-sample) fit for y_t .

Agnostic Approach

Use these data in **factor-augmented** regressions:

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

$f_{1,t}, \dots, f_{r,t}$: dynamic factors from large data set through:

- **Principal Components (PC)**: extract linear combinations of predictors that provides the best description of the large data set.
- **Partial Least Squares (PLS) regression**: extract orthogonal linear combinations of predictors that have maximum explanatory power for $\Delta p_{t+h,t}$.
- Use modified BIC to select r and k . See Groen and Kapetanios (2009b).

Agnostic Approach

Use these data in **factor-augmented** regressions:

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

$f_{1,t}, \dots, f_{r,t}$: dynamic factors from large data set through:

- **Principal Components (PC)**: extract linear combinations of predictors that provides the best description of the large data set.
- **Partial Least Squares (PLS) regression**: extract orthogonal linear combinations of predictors that have maximum explanatory power for $\Delta p_{t+h,t}$.
- Use modified BIC to select r and k . See Groen and Kapetanios (2009b).

Agnostic Approach

Use these data in **factor-augmented** regressions:

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

$f_{1,t}, \dots, f_{r,t}$: dynamic factors from large data set through:

- **Principal Components (PC)**: extract linear combinations of predictors that provides the best description of the large data set.
- **Partial Least Squares (PLS) regression**: extract orthogonal linear combinations of predictors that have maximum explanatory power for $\Delta p_{t+h,t}$.

•

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

Data I

10 Forecast variables:

- Commodity Research Bureau (CRB): both overall index and industrial metals sub-index start from 1973.
- S&P/Goldman Sachs Index (SPG): overall from 1973, industrial metals and energy sub-indices start in 1977 and 1983, respectively.
- IMF Non-fuel Commodity Prices Index (IMF) starts in 1980 along with the IMF industrial metals sub-index.
- Dow Jones-AIG Commodity Index (DJAIG): from 1991, along with its sub-indices for energy and metals.

Data II

Predictor variables:

Cross-sectional sizes of panels vary depending on time span of underlying index.

- CRB and SPG aggregate: 1973.03-2009.2 with total of $N = 96$ series in the panel.
- SPG industrial metals sub-index: 1977.02-2009.2 with $N = 112$
- SPG energy sub-index: 1983.02-2009.02 with $N = 127$.
- IMF: 1980.02-2009.02 with $N = 122$.
- DJAIG: 1991.02-2009.02, with $N = 143$.

Forecasting: Methodology

- All models sequentially re-estimated using a fixed rolling data window of 120 monthly observations.
- After each re-estimation we generate a forecast h -month ahead. [▶ Details](#)
- We then report the relative MSE differentials as:

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

with $B = AR$ or RW .

MSE_F^{adj} : Clark and West (2006, 2007) finite sample correction for spurious noise in MSE of the fundamentals-based predictions resulting from inappropriately fitting a larger model on the data.

Forecasting: Methodology

- All models sequentially re-estimated using a fixed rolling data window of 120 monthly observations.
- After each re-estimation we generate a forecast h -month ahead. [▶ Details](#)
- We then report the relative MSE differentials as:

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

with $B = AR$ or RW .

MSE_F^{adj} : Clark and West (2006, 2007) finite sample correction for spurious noise in MSE of the fundamentals-based predictions resulting from inappropriately fitting a larger model on the data.

Forecasting: Methodology

- All models sequentially re-estimated using a fixed rolling data window of 120 monthly observations.
- After each re-estimation we generate a forecast h -month ahead. [▶ Details](#)
- We then report the relative MSE differentials as:

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

with $B = AR$ or RW .

$$MSE_F^{adj} = MSE_F - \left(\frac{1}{T - t_0 - h} \sum_{s=t_0}^{T-h} \left(\Delta \hat{p}_{s,s+h}^B - \Delta \hat{p}_{s,s+h}^F \right)^2 \right)$$

- We test $H_0: MSE_B - MSE_F^{adj} = 0$ versus $H_1: MSE_B - MSE_F^{adj} > 0$.

Forecasting: Methodology

- All models sequentially re-estimated using a fixed rolling data window of 120 monthly observations.
- After each re-estimation we generate a forecast h -month ahead. [▶ Details](#)
- We then report the relative MSE differentials as:

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

with $B = AR$ or RW .

$$MSE_F^{adj} = MSE_F - \left(\frac{1}{T - t_0 - h} \sum_{s=t_0}^{T-h} \left(\Delta \hat{p}_{s,s+h}^B - \Delta \hat{p}_{s,s+h}^F \right)^2 \right)$$

- We test $H_0: MSE_B - MSE_F^{adj} = 0$ versus $H_1: MSE_B - MSE_F^{adj} > 0$.

Forecasting: Methodology

- All models sequentially re-estimated using a fixed rolling data window of 120 monthly observations.
- After each re-estimation we generate a forecast h -month ahead. [▶ Details](#)
- We then report the relative MSE differentials as:

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

with $B = AR$ or RW .

- We test $H_0: MSE_B - MSE_F^{adj} = 0$ versus
 $H_1: MSE_B - MSE_F^{adj} > 0$.

$$z_{MSE}^{adj} = (T - t_0 - h)^{\frac{1}{2}} \left(\frac{MSE_B - MSE_F^{adj}}{\left(Var \left(\tilde{u}_{t+h}^{adj} \right) \right)^{\frac{1}{2}}} \right) \sim N(0, 1)$$

And the winner is ...

There is no obvious winner!

- Information from large panels of global economic variables can help, but their forecasting properties are by no means overwhelming.
- No overwhelming evidence for the notion that commodity currencies are useful predictors. Even less empirical support for commodity futures.
- Across 10 commodity indices no easy patterns or generalizations are found

Some Specific Results ...

for CRB Aggregate and IMF Non-Fuel
Commodity Price Indices

Forecasting the CRB Aggregate Index: 1973.03 - 2009.02

<i>h</i>	<u>CRR</u>		<u>PC Regression</u>		<u>PLS Regression</u>	
	<i>RW</i>	<i>AR</i>	<i>RW</i>	<i>AR</i>	<i>RW</i>	<i>AR</i>
1	0.07 (1.34)*	-0.01 (-0.56)	0.00 (0.03)	-0.01 (-0.63)	0.20 (1.86)**	0.14 (0.99)
3	0.02 (0.34)	0.02 (0.59)	-0.02 (-0.88)	0.00 (-0.16)	0.14 (1.28)*	0.14 (0.82)
6	0.02 (0.25)	0.05 (1.14)	-0.06 (-0.71)	-0.02 (-0.55)	-0.10 (-0.56)	-0.09 (-0.73)
12	0.02 (0.25)	0.06 (0.93)	-0.09 (-0.85)	-0.02 (-0.24)	0.00 (0.00)	0.02 (0.16)
24	-0.01 (-0.08)	0.07 (1.56)*	-0.19 (-1.97)	-0.05 (-0.57)	-0.59 (-2.84)	-0.48 (-2.40)

Forecasting the IMF Non-Fuel Index: 1980.02 - 2009.02

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

Sensitivity Test I

Is the extra information of the PLS-based factor model *vis-à-vis* the CRR model significant enough to warrant its use?

Test whether out-of-sample

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

is better than

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

Sensitivity Test I

h	1	3	6	12	24
CRB Aggregate	0.18 (1.44)*	0.25 (1.95)**	-0.05 (-0.41)	0.14 (1.43)*	-0.09 (-0.37)
IMF Non-Fuel	0.17 (1.48)*	0.14 (1.31)*	-0.06 (-0.24)	0.23 (0.83)	-0.03 (-0.26)

The PLS-based factor model has a slight edge over the CRR model.

Sensitivity Test II

Consistent time series on a broad set of commodity futures and forward rates for 1-, 3-, 6- and 12-months ahead horizons are only available from the mid-1980s onwards. We are forced to limit this experiment to the DJ-AIG price indices.

What are the results?

The forecasting performances are basically unchanged when we add these futures and forwards to the relevant predictor variable panels. Thus, qualitatively, the factor-augmented model results relative to the naive benchmark models remain similar.

Sensitivity Test II

Consistent time series on a broad set of commodity futures and forward rates for 1-, 3-, 6- and 12-months ahead horizons are only available from the mid-1980s onwards. We are forced to limit this experiment to the DJ-AIG price indices.

What are the results?

The forecasting performances are basically unchanged when we add these futures and forwards to the relevant predictor variable panels. Thus, qualitatively, the factor-augmented model results relative to the naive benchmark models remain similar.

The DJ-AIG Aggregate Index without futures: 1973.03 - 2009.02

h	PC Regression		PLS Regression	
	RW	AR	RW	AR
1	0.19 (0.58)	0.03 (0.63)	0.40 (0.60)	0.18 (1.03)
3	0.00 (0.05)	0.03 (1.06)	0.48 (0.94)	0.48 (0.93)
6	-0.08 (-0.22)	0.03 (0.55)	0.06 (1.31)*	0.17 (0.80)
12	0.25 (0.84)	0.34 (1.33)*	0.20 (0.62)	0.33 (0.86)
24	0.62 (2.14)**	0.82 (1.80)**	0.04 (0.07)	0.08 (0.19)

The DJ-AIG Aggregate Index with futures: 1973.03 - 2009.02

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

Conclusions

- **Basic message: inconclusiveness.**
- Information from a large global economic data panel can help when PLS is used ...
- ... but as of yet the forecasting properties are by no means overwhelming.
- **Policy lessons:**
 - Commodity price forecasts provide only highly noisy hints about their actual future trajectories and persistence.
 - Excessive confidence in such forecasts may bias policymakers' views and beliefs about future inflation risks.

Conclusions

- Basic message: inconclusiveness.
- Information from a large global economic data panel can help when PLS is used ...
- ... but as of yet the forecasting properties are by no means overwhelming.
- Policy lessons:
 - Commodity price forecasts provide only highly noisy hints about their actual future trajectories and persistence.
 - Excessive confidence in such forecasts may bias policymakers' views and beliefs about future inflation risks.

Conclusions

- Basic message: inconclusiveness.
- Information from a large global economic data panel can help when PLS is used ...
- ... but as of yet the forecasting properties are by no means overwhelming.
- **Policy lessons:**
 - Commodity price forecasts provide only highly noisy hints about their actual future trajectories and persistence.
 - Excessive confidence in such forecasts may bias policymakers' views and beliefs about future inflation risks.

Details Sequential Updating for Forecasting

1. For any horizon h generate first forecast on $t_0 = \omega$.
2. Extract r^{max} PC and PLS factors from N predictor variables over the sample $t = t_0 - \omega + 1, \dots, t_0 - h$.
3. Determine for $t = t_0 - \omega + 1, \dots, t_0 - h$ the optimal lag order and number of factors using BICM across $j = 0, \dots, k^{max} = 12$ and $i = 1, \dots, r^{max} = 6$. Gives $(\hat{k}_{BICM}^{PC}, \hat{r}_{BICM}^{PC})$ and $(\hat{k}_{BICM}^{PLS}, \hat{r}_{BICM}^{PLS})$. Similarly, use BIC for optimal lag order in AR benchmark and CRR model.
4. Given the outcome of step 3, estimate over the sample $t = t_0 - \omega + 1, \dots, t_0 - h$.
5. Extract \hat{r} PC and PLS factors from the N predictor variables over the sample $t = t_0 - \omega + 1, \dots, t_0$.
6. Generate forecast $\Delta \hat{p}_{t+h,t}$ using the estimated dimensions from step 3, the parameter estimates from step 4, and factors from step 5.
7. Repeat for $t_0 = \omega + 1, \dots, T - h$ and for any forecast horizon h .