BEAR 4.2

Introducing Stochastic Volatility, Time Varying Parameters and Time Varying Trends

A. Dieppe R. Legrand B. van Roye

ECB

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The views expressed in this presentation are the authors and do not necessarily reflect those of the ECB.

Short recap of BEAR

BEAR is a comprehensive (Bayesian) (Panel) VAR toolbox (based on MATLAB) for Research and Policy analysis.

Aim to satisfying 3 main objectives:

1. Easy to understand, augment and adapt. Keep constantly developed further to always be at the frontier of economic research.
2. Comprehensive: all applications (basic and advanced) gathered in one single application.
3. Easy to use for desk economists and non-technical users thanks to a user-friendly graphical interface and user's guide.

Short recap of BEAR: Version 3.0

4 estimation types of VAR models

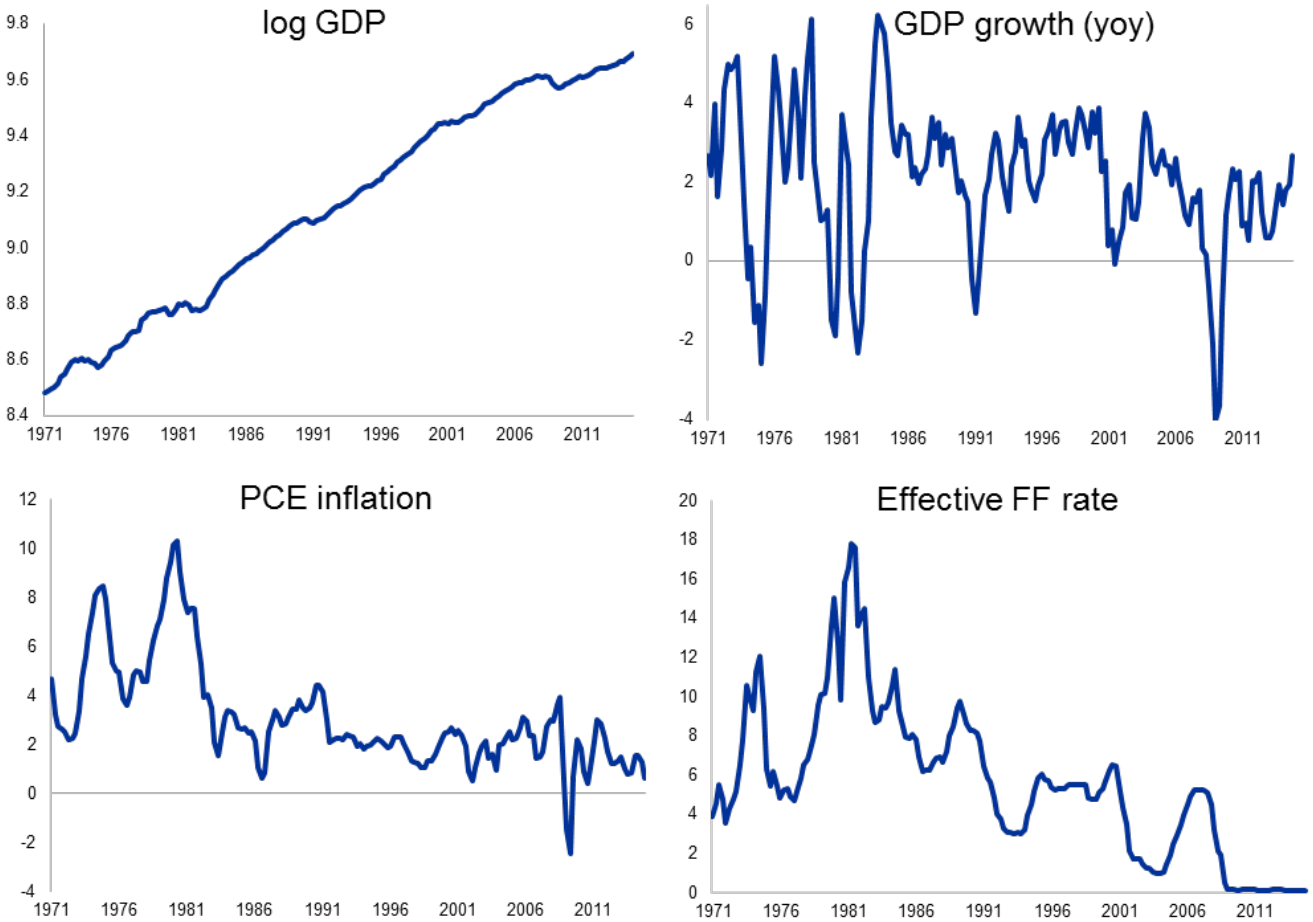
1. OLS (maximum likelihood) VAR
2. Standard Bayesian VAR
   - Many prior distributions
3. Mean-adjusted Bayesian VAR (Villani, 2009)
   - Informative prior on the steady-state
4. Panel VAR
   - adds a cross-sectional dimension

What's new? BEAR 4.0

1. OLS (maximum likelihood) VAR
2. Standard Bayesian VAR
   - added priors for the long run (Giannone et al. 2017)
3. Mean-adjusted Bayesian VAR (Villani 2009)
   - extended to a more flexible setup with trends and regime changes
4. Panel VAR (Ciccarrelli and Canova 2013)
   - added sign restrictions for structural identification
5. Stochastic Volatility
6. Time Varying Parameters
7. New forecast evaluation tests
8. Efficiency gains (parallelisation in sign restrictions procedure)

Data for examples

- US real GDP (log-levels or growth rates)
- US Personal Consumption Expenditure Index (y-o-y)
- US Effective Federal Funds rate



Motivation

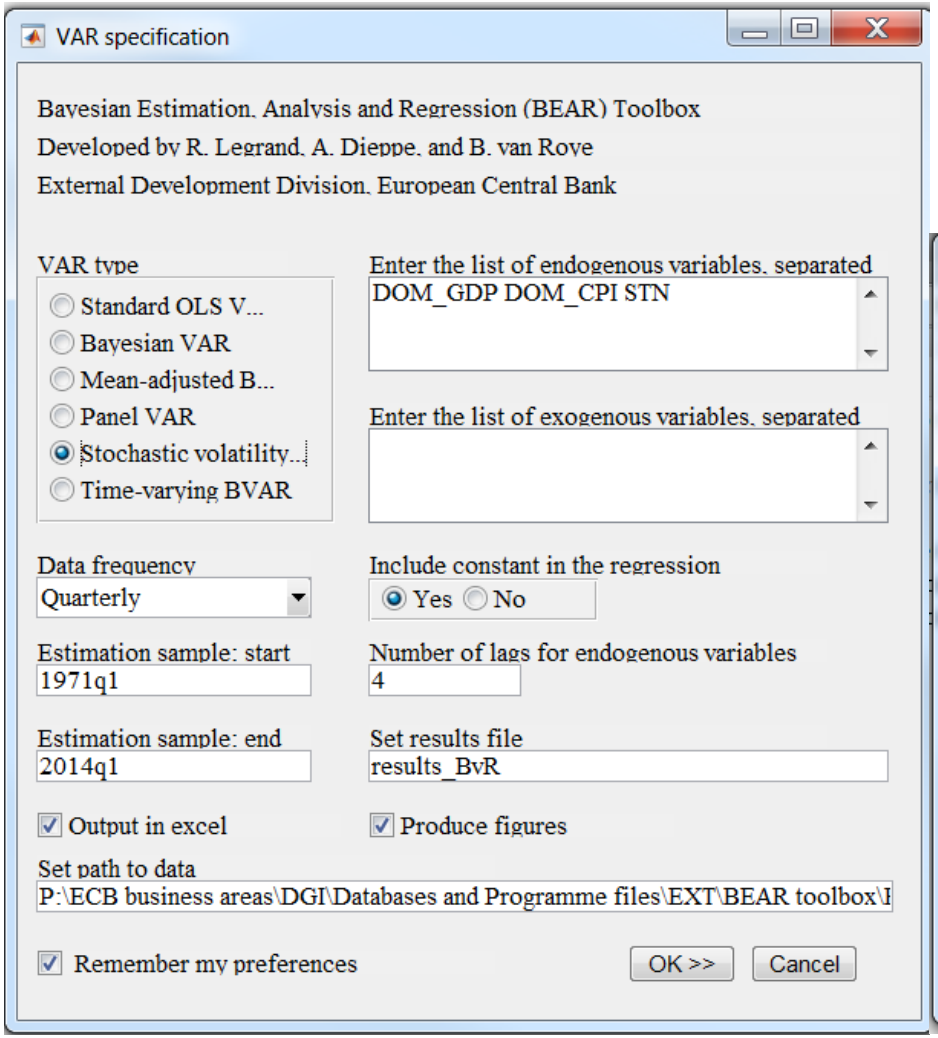
- A data-generating process of economic variables often seems to have drifting coefficients and shocks of stochastic volatility.
- In particular, VAR innovation variances change over time (Bernanke and Mihov 1998, Kim and Nelson 1999, MacConnell and Perez Quiros 2000).

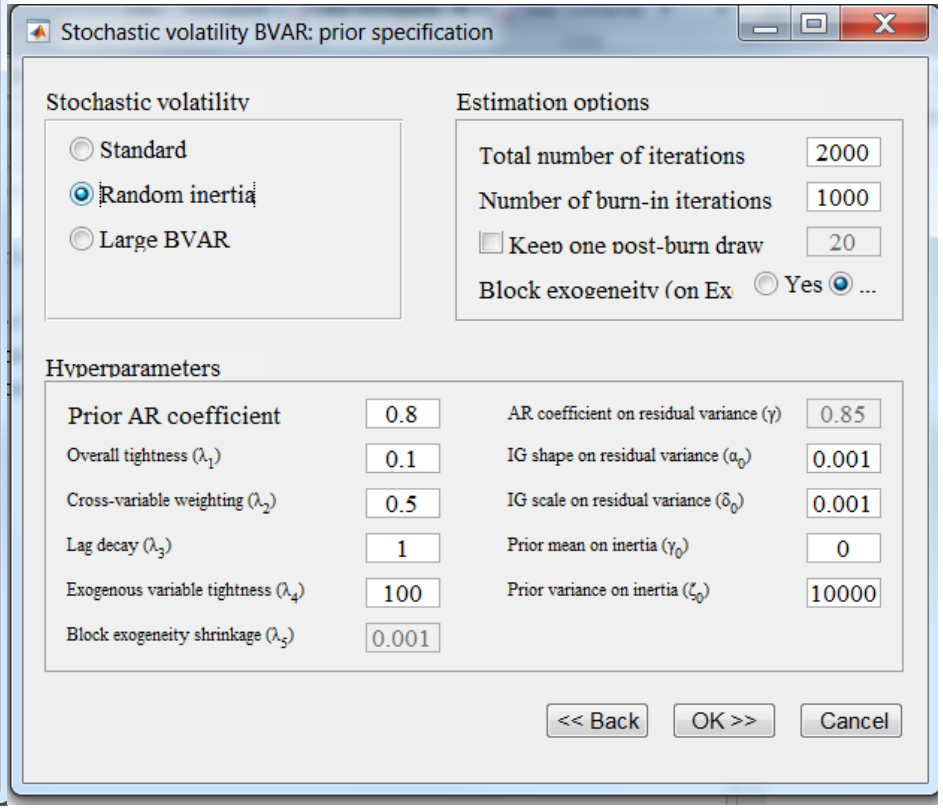
Setup in BEAR

- Cogley and Sargent (2005)
- Sparse matrix approach (Chan and Jeliazkov 2009)
- Three options: 1.) Standard, 2.) Random inertia, 3.) Large BVARs (Carriero, Clark and Marcellino 2012)

Stochastic Volatility

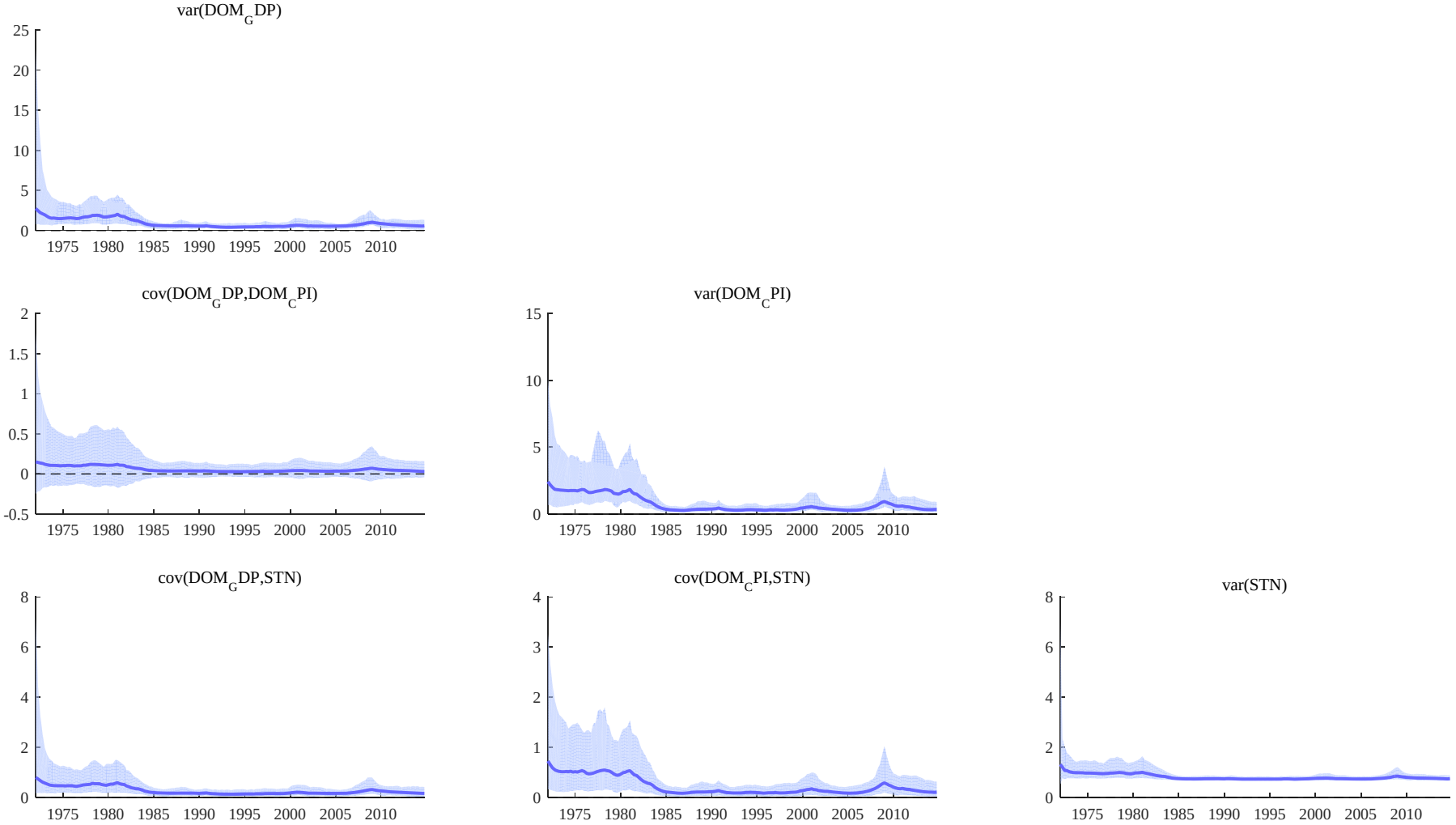
Implementation in BEAR





Stochastic Volatility

Example output



Time Varying Parameters

Motivation and setup in BEAR

Motivation

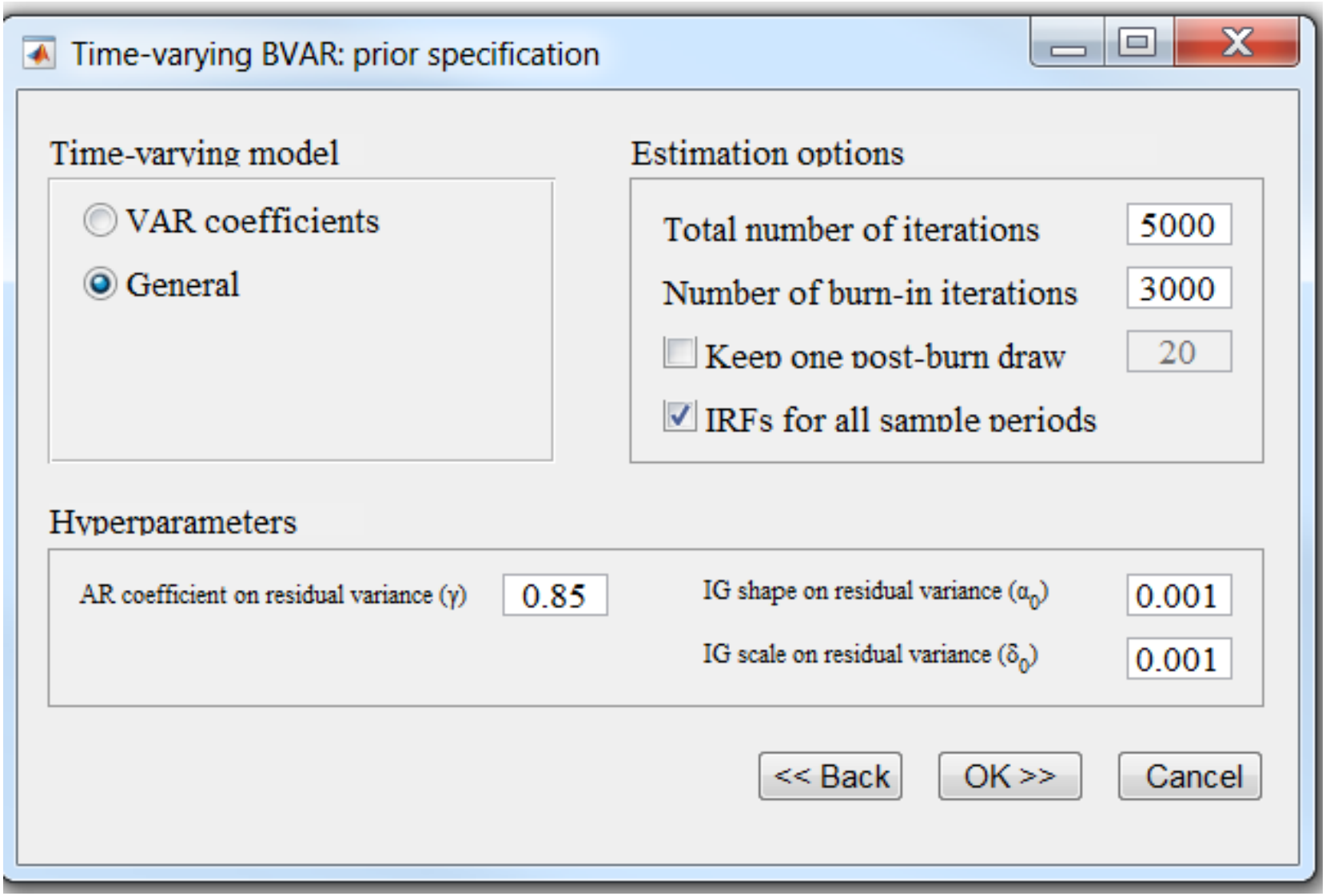
- "There is strong evidence that U.S. unemployment and inflation were higher and more volatile in the period between 1965 and 1980 than in the last 20 years." (Primiceri 2005, RES).
- Typical questions in ECB policy analysis: Has the Phillips curve flattened? Has the monetary policy transmission channel changed?

Set-up in BEAR

- Sparse matrix approach (Chan and Jeliazkov 2009)
- Two options: 1.) Time varying VAR coefficients 2.) General (Time varying VAR coefficients and Stochastic Volatility)

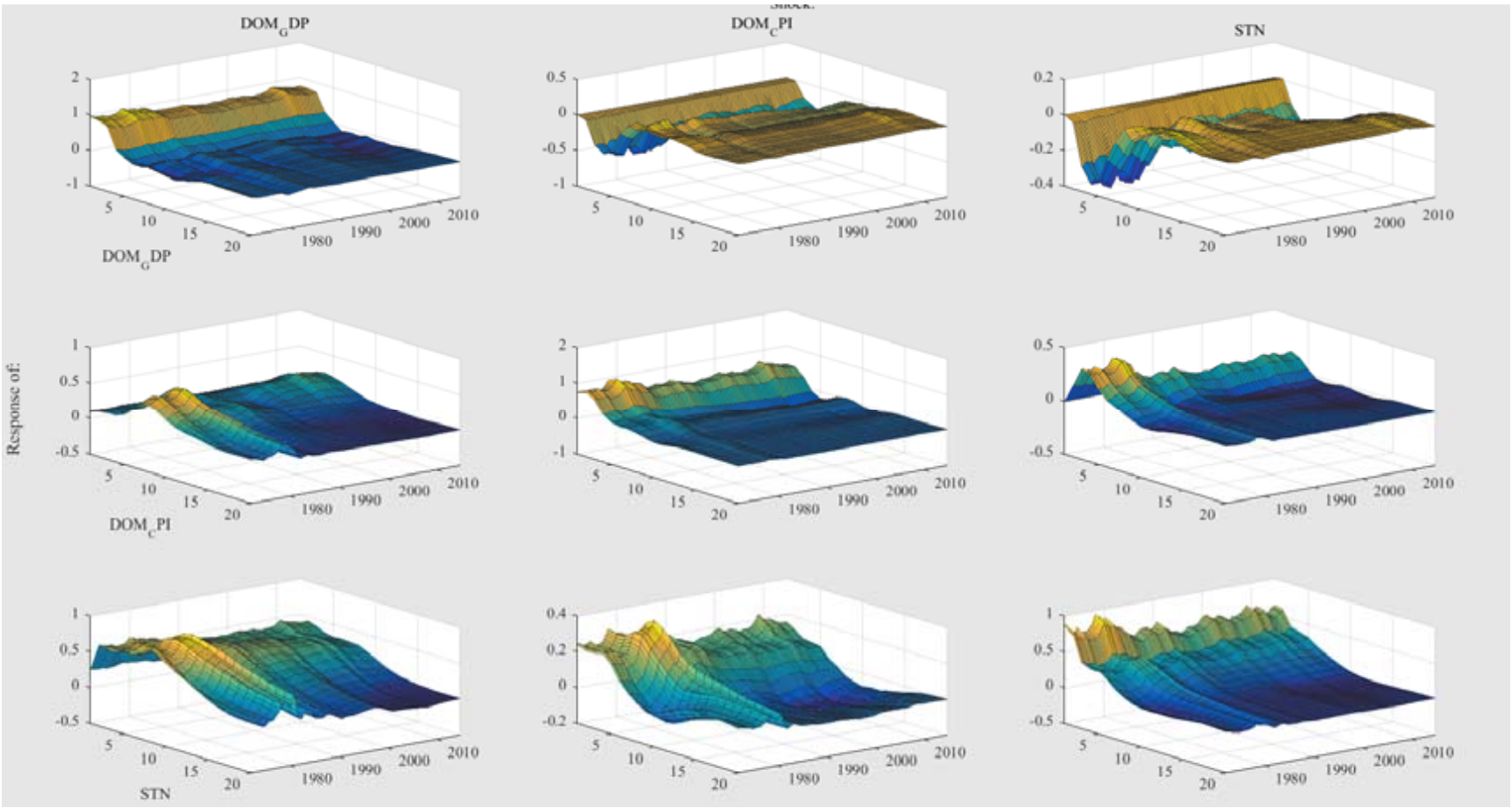
Time Varying Parameters

Implementation in BEAR



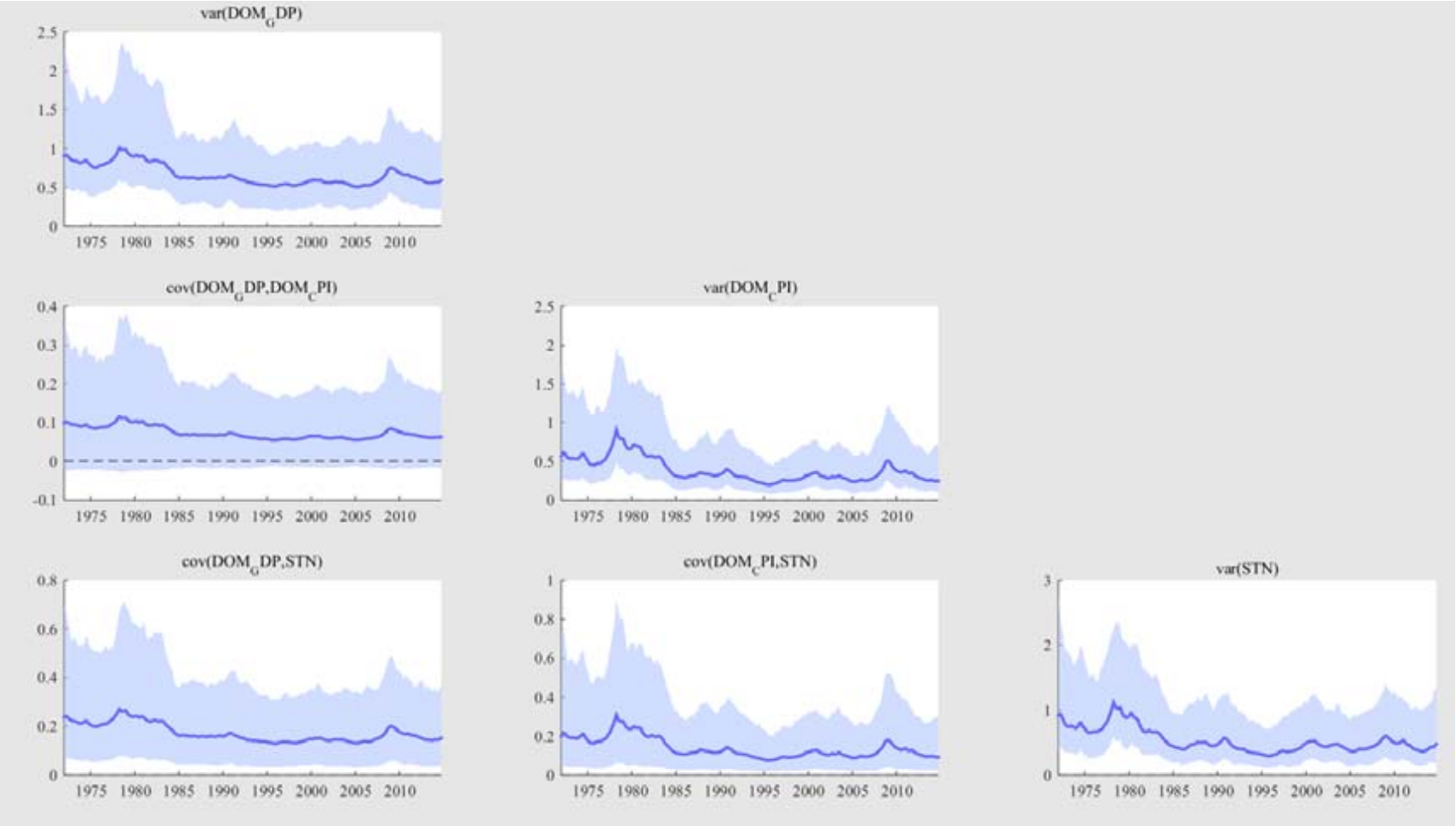
Time Varying Parameters

Example output



Time Varying Parameters

Example output



Equilibrium VARs

Motivation and setup in BEAR

Motivation

- Usually we are interested in trend-cycle decompositions.
- For historical decompositions we want to calculate deviations from "steady-state".
- So we have to take into account the "long-run", the "equilibrium", "steady-state", "trends" or "fundamentals".

Set-up in BEAR

- We extent the methodology of Villani (2009).
- In Version 4.0 it is possible to have a prior on the deterministic part (constant, linear trend, quadratic trend).
- A generalization to stochastic trends will be part of the next version.

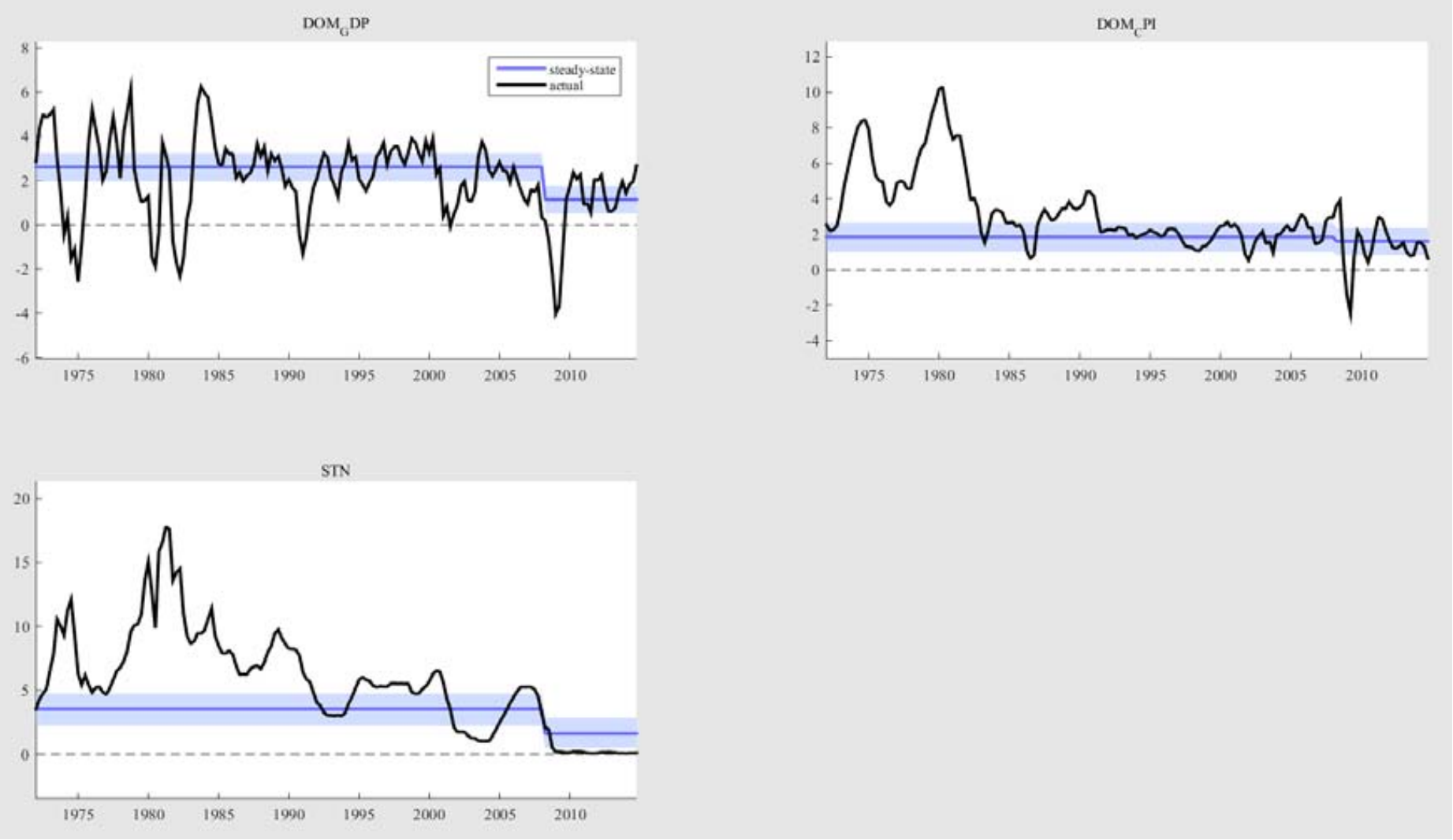
Equilibrium VARs

Implementation in BEAR

A	B	C	D	E	F
		trend	trend prior	regime 1	trend prior 2
	DOM_GDP	1	0 5	2008q2 2014q4	0 2
	DOM_CPI	1	1 4	2008q2 2014q4	0 2
	STN	1	2 5	2008q2 2014q4	0 3

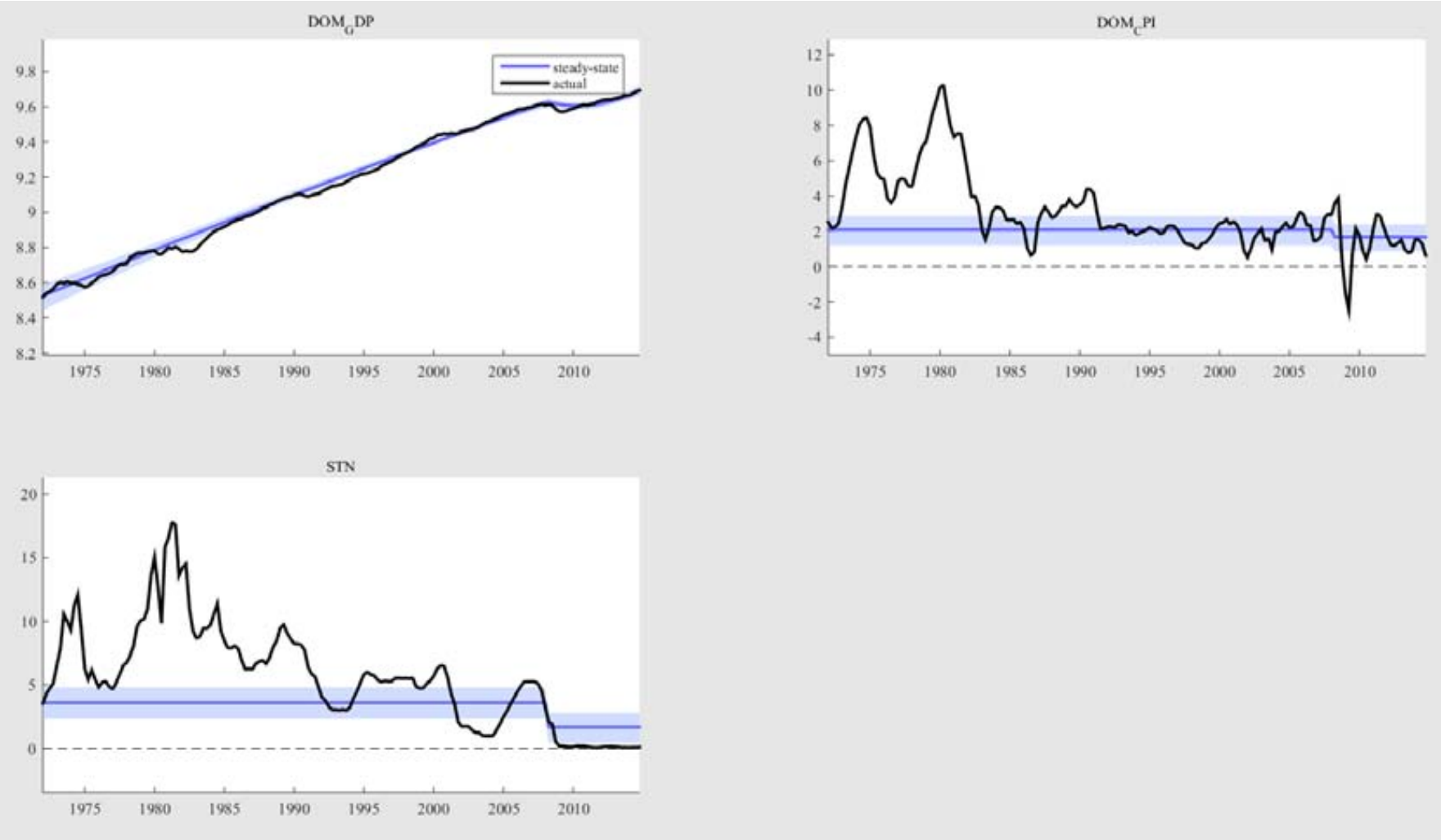
Equilibrium VARs

Example output



Equilibrium VARs

Example output



Priors for the long-run

Motivation and setup in BEAR

Motivation

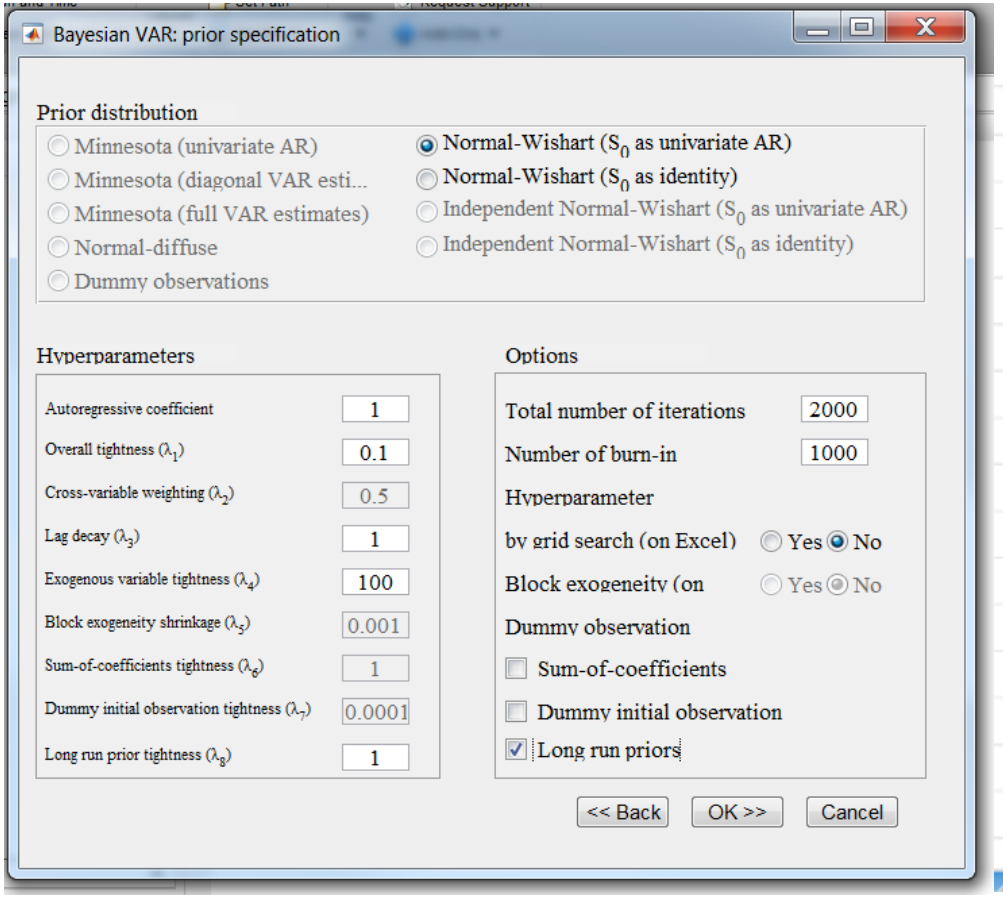
- Disciplination the long-run predictions of VARs.
- "Flat-prior VARs tend to attribute an implausibly large share of the variation in observed time series to a deterministic—and thus entirely predictable—component." (Giannone et al. 2017)
- Priors can be naturally elicited using economic theory, which provides guidance on the joint dynamics of macroeconomic time series in the long run.

Set-up in BEAR

- Giannone, Lenza and Primiceri (2017).
- Conjugate prior, easily implemented using dummy observations and combined with other popular priors.

Priors for the long-run

Implementation in BEAR

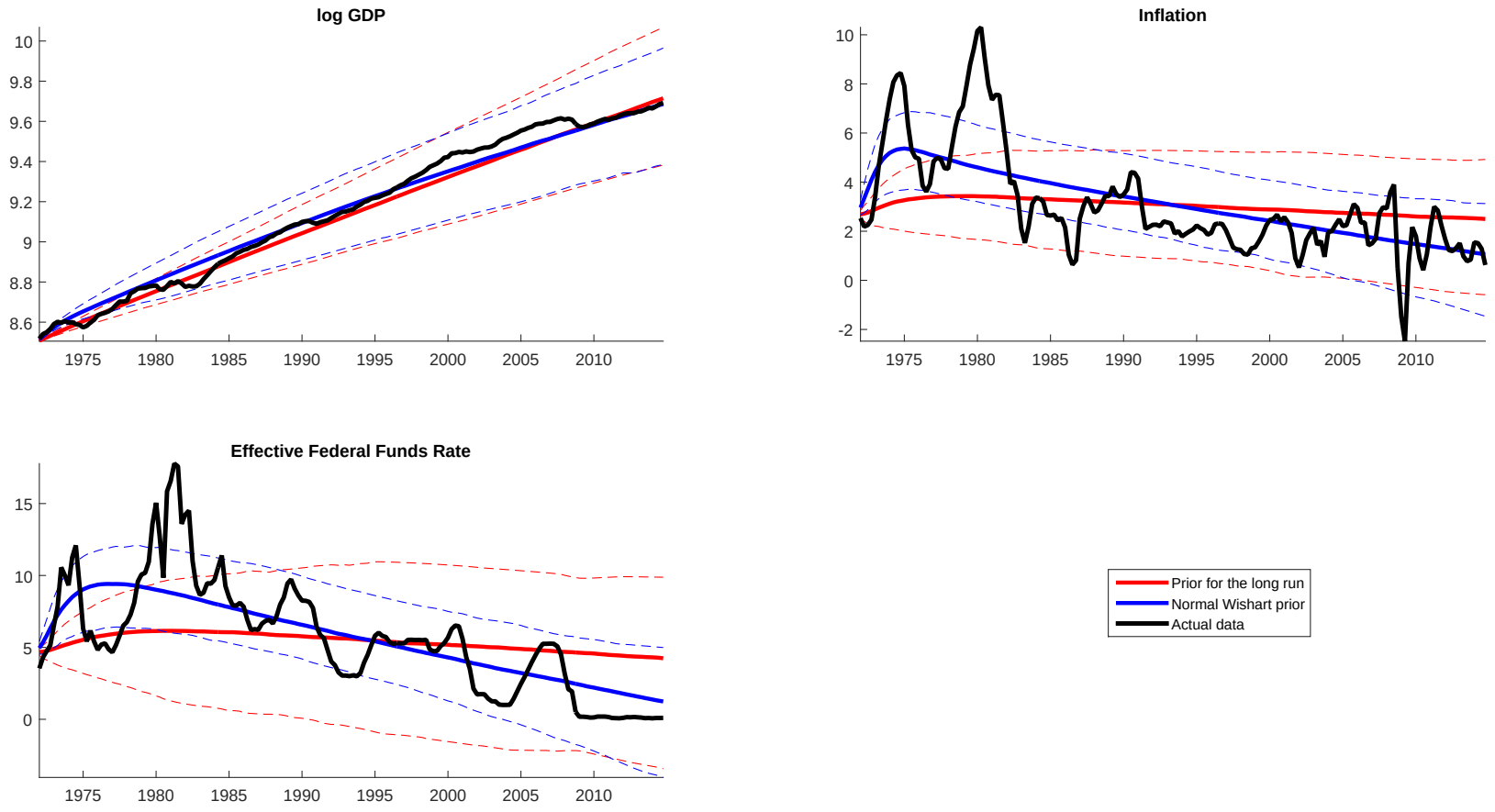


	DOM_GDP	DOM_CPI	STN	
DOM_GDP	1	0	0	real trend
DOM_CPI	0	1	1	nominal trend
STN	0	-1	1	real interest rate

EA UK yearly quarterly monthly weekly daily undated mean adj prior Long run prior

Priors for the long-run

Example output



Forecasting evaluation procedures

Motivation and setup in BEAR

Motivation

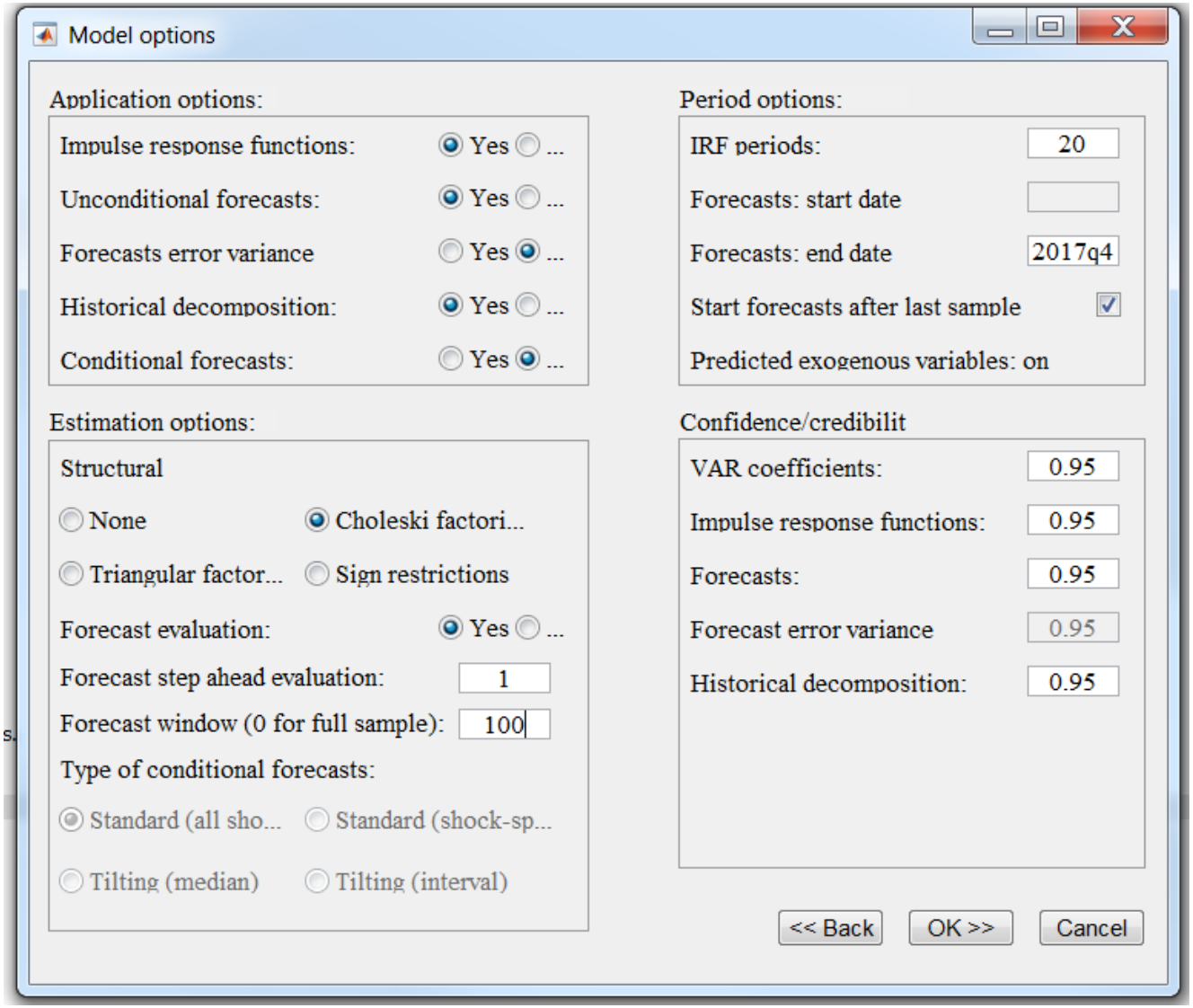
- Assess forecasting performance of our VAR.
- Large literature has provided important insights on how to test whether forecasts are optimal / rational.
- Traditional tests that are based on stationarity assumptions should not be used in the presence of instabilities.

Set-up in BEAR

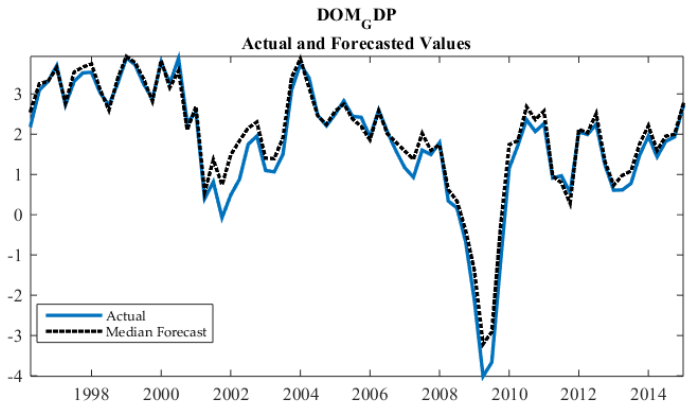
- Rossi and Sekhposyan (2016, 2017) and Loria and Rossi (2017).
- Rolling window estimations with density and point forecast evaluation.

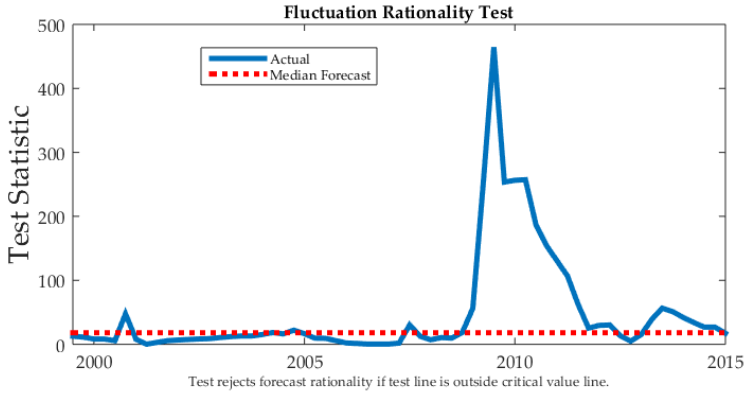
Forecasting evaluation procedures

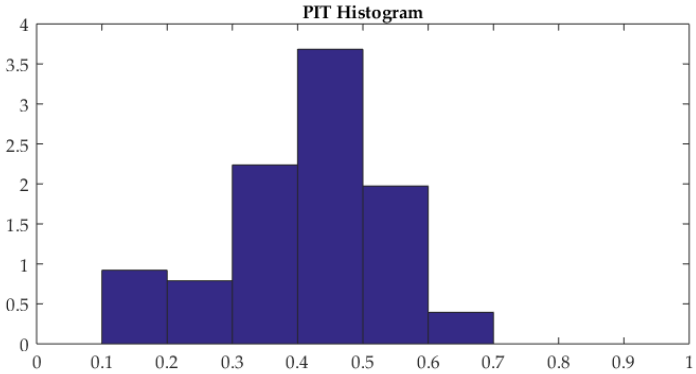
Implementation in BEAR

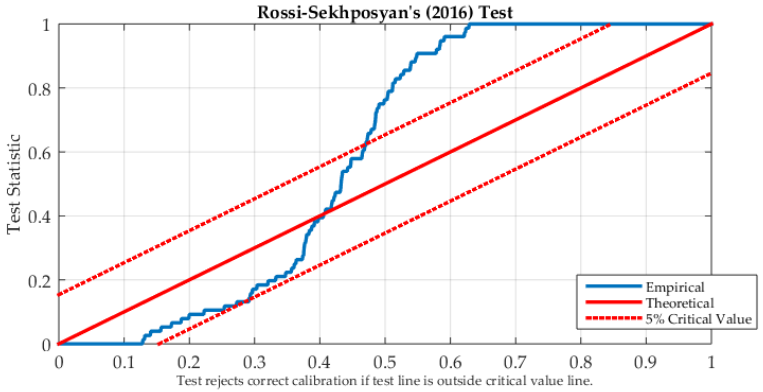


Forecasting evaluation procedures









Other improvements

- Sign restrictions for panel VAR models (pooled and hierarchical models)
- Introduced the DIC criterion
- IRFs to exogenous variables
- Parallelisation for some procedures (sign restrictions, tilting)
- Option to suppress figures and excel output (efficiency gains)

Envisaged toolbox extensions

Further non-linear BVARs

- Threshold BVAR (Chiu and Hoke 2016)
- Markov-Switching BVAR (Sims, Waggoner and Zha 2008)

Sign restrictions

- Baumeister and Hamilton (2015)
- Narrative sign restrictions (Antolin-Diaz and Rubio-Ramirez 2016)

Mixed frequency VARs (Schorfheide and Song 2016)

Open discussion / feedback session

- BEAR 4.2 is open source: code available on the ECB website
- Suggestions for improvements

- Questions and answers

Stochastic volatility

Some background

The model includes n endogenous variables, m exogenous variables and p lags, and is estimated over T time periods. In compact form, it writes:

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + ... + A_p y_{t-p} + C x_t + \varepsilon_t \tag{1}$$

It is assumed that the residuals are distributed according to:

$$\varepsilon_t \sim \mathcal{N}(0, \Sigma_t) \tag{2}$$

$$\Sigma_t = F \Lambda_t F' \tag{3}$$

and

$$\lambda_{i,t} = \gamma_{(i)} \lambda_{i,t-1} + \upsilon_{i,t} \qquad \upsilon_{i,t} \sim \mathcal{N}(0, \phi_i) \tag{4}$$

Time Varying Parameters

Some background

$$y_t = A_{1,t}y_{t-1} + A_{2,t}y_{t-2} + ... + A_{p,t}y_{t-p} + Cx_t + \varepsilon_t \tag{5}$$

The VAR coefficients are assumed to follow the following autoregressive process:

$$\beta_t = \beta_{t-1} + \nu_t \qquad , \qquad \nu_t \sim N(0, \Omega) \tag{6}$$

$$\varepsilon_t \sim \mathcal{N}(0, \Sigma_t) \tag{7}$$

$$\Sigma_t = F\Lambda_t F' \tag{8}$$

Equilibrium VARs

Some background

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + C x_t + \varepsilon_t \ , \text{ where } t = 1, 2, ..., T \quad (9)$$

This model may rewrite as:

$$y_t = A(L)^{-1} C x_t + \Psi_0 \varepsilon_t + \Psi_1 \varepsilon_{t-1} + \Psi_2 \varepsilon_{t-2} ... \quad (10)$$

with $A(L) = I - A_1 L - A_2 L^2 \ldots A_p L^p$ the matrix lag polynomial representation of 9. Villani (2009) proposes an alternative:

$$A(L)(y_t - F x_t) = \varepsilon_t \quad (11)$$

Reformulation of the model with stochastic/deterministic time-varying steady-state values. Generalisation of Villani (2009), following Akkaya et al. (2017) with a time varying F matrix:

$$A(L)(y_t - F_t x_t) = \varepsilon_t \quad (12)$$

Priors for the long run

Some background

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + ... + A_p y_{t-p} + C x_t + \varepsilon_t \tag{13}$$

$$\varepsilon_t \sim \mathcal{N}(0, \Sigma) \tag{14}$$

The model can be rewritten in terms of levels and differences:

$$\Delta y_t = \Pi y_{t-1} + \Lambda_1 \Delta y_{t-1} + ... + \Lambda_{p-1} \Delta y_{t-p} + C x_t + \varepsilon_t \tag{15}$$

where $\Pi = (A_1 + \cdots + A_p) - I_n$ and $\lambda_j = -(A_{j+1} \dots) + A_p$, with $j = 1, \dots, p-1$.
Prior for Π:

$$\Delta y_t = \Gamma \tilde{y}_{t-1} + \Lambda_1 \Delta y_{t-1} + ... + \Lambda_{p-1} \Delta y_{t-p} + C x_t + \varepsilon_t \tag{16}$$

where $\tilde{y}_{t-1} = H y_{t-1}$.

$$\Gamma_{.i} | H_{i.}, \Sigma \sim \mathcal{N}\Big(0, \lambda_8(H_{i.})\Sigma\Big) \tag{17}$$