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

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

VAR specification

Bayesian Estimation, Analysis and Regression (BEAR) Toolbox
Developed by R. Legrand, A. Dieppe, and B. van Roye
External Development Division, European Central Bank

VAR type
- Standard OLS
- Bayesian VAR
- Mean-adjusted BVAR
- Panel VAR
- Stochastic volatility
- Time-varying BVAR

Enter the list of endogenous variables, separated
DOM_GDP DOM_CPI STN

Enter the list of exogenous variables, separated

Data frequency
Quarterly

Estimation sample: start 1971q1
Estimation sample: end 2014q1

Include constant in the regression
- Yes
- No

Number of lags for endogenous variables
4

Set results file
results_BVAR

Output in excel
- Yes
- No

Set path to data
P:\ECB business areas\DGI\Databases and Programme files\EXT-BEAR toolbox\%

OK >> Cancel

Stochastic volatility

- Standard
- Random inertia
- Large BVAR

Prior AR coefficient
- 0.8
- 0.1
- 0.5
- 1
- 100
- 0.001

AR coefficient on residual variance (γ)
- 0.85
- 0.001

IG shape on residual variance (α)
- 0.001

IG scale on residual variance (β)
- 0.001

Prior mean on inertia (y)
- 0

Prior variance on inertia (y)
- 10000

Estimation options
- Total number of iterations
- Number of burn-in iterations
- Keep one post-burn draw

Block exogeneity shrinkage (β)
- 0.001

<< Back OK >> Cancel
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

![Image of BEAR GUI for time-varying BVAR: prior specification]

- **Time-varying model**
  - VAR coefficients
  - General

- **Estimation options**
  - Total number of iterations: 5000
  - Number of burn-in iterations: 3000
  - Keep one post-burn draw: 20
  - IRFs for all sample periods

- **Hyperparameters**
  - AR coefficient on residual variance ($\gamma$): 0.85
  - IG shape on residual variance ($\alpha_0$): 0.001
  - IG scale on residual variance ($\delta_0$): 0.001
Time Varying Parameters

Example output
Time Varying Parameters

Example output
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

<table>
<thead>
<tr>
<th></th>
<th>trend</th>
<th>trend prior</th>
<th>regime 1</th>
<th>trend prior 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>DOM_GDP</td>
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<td>0.5</td>
<td>2008q2 2014q4</td>
<td>0.2</td>
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<tr>
<td>DOM_CPI</td>
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<td>2008q2 2014q4</td>
<td>0.2</td>
</tr>
<tr>
<td>STN</td>
<td>1</td>
<td>2.5</td>
<td>2008q2 2014q4</td>
<td>0.3</td>
</tr>
</tbody>
</table>
Equilibrium VARs

Example output
Equilibrium VARs

Example output
Motivation

- Disciplinisation 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

- Conjugate prior, easily implemented using dummy observations and combined with other popular priors.
Priors for the long-run implementation in BEAR

[Image of a window with prior specification settings]

- **Prior distribution**:
  - Minnesota (univariate AR)
  - Minnesota (diagonal VAR estimates)
  - Minnesota (full VAR estimates)
  - Minnesota (ARMA)
  - Minnesota (univariate)
  - Normal-Wishart (S_0 as univariate AR)
  - Normal-Wishart (S_0 as identity)
  - Independent Normal-Wishart (S_0 as univariate AR)
  - Independent Normal-Wishart (S_0 as identity)
  - Dummy-diffuse
  - Dummy-diffuse

- **Hyperparameters**
  - Autoregressive coefficient
  - Overall tightness (λ_1)
  - Cross-variable weighting (λ_2)
  - Lag decay (λ_3)
  - Endogenous variable tightness (λ_4)
  - Block exogeneity shrinkage (λ_5)
  - Sum-of-coefficients tightness (λ_6)
  - Dummy initial observation tightness (λ_7)
  - Long-run prior tightness (λ_8)

- **Options**
  - Total number of iterations: 2000
  - Number of burn-in: 1000
  - Hyperparameter
  - By grid search (on Excel): Yes
  - Block exogeneity: Yes
  - Dummy observation
    - Sum-of-coefficients
    - Dummy initial observation
    - Long-run prior

[Table]

<table>
<thead>
<tr>
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<th>DOM_CPI</th>
<th>STN</th>
</tr>
</thead>
<tbody>
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<td>DOM_GDP</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>DOM_CPI</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>STN</td>
<td>0</td>
<td>-1</td>
<td>1</td>
</tr>
</tbody>
</table>

- real trend
- nominal trend
- real interest rate
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**
- Rolling window estimations with density and point forecast evaluation.
Forecasting evaluation procedures
Implementation in BEAR

Model options

Application options:
- Impulse response functions: Yes
- Unconditional forecasts: Yes
- Forecasts error variance: Yes
- Historical decomposition: Yes
- Conditional forecasts: Yes

Period options:
- IRF periods: 20
- Forecasts: start date
- Forecasts: end date: 2017q4
- Start forecasts after last sample: Yes
- Predicted exogenous variables: on

Estimation options:

Structural
- None
- Triangular factor...
- Sign restrictions
- Forecast evaluation: Yes
- Forecast step ahead evaluation: 1
- Forecast window (0 for full sample): 100

Type of conditional forecasts:
- Standard (all shocks)
- Tilting (median)

Confidence/credibility:
- VAR coefficients: 0.95
- Impulse response functions: 0.95
- Forecasts: 0.95
- Forecast error variance: 0.95
- Historical decomposition: 0.95
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:

\[
y_t = A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + C x_t + \varepsilon_t
\]  

(1)

It is assumed that the residuals are distributed according to:

\[
\varepsilon_t \sim \mathcal{N}(0, \Sigma_t)
\]  

(2)

\[
\Sigma_t = F \Lambda_t F',
\]  

(3)

and

\[
\lambda_{i,t} = \gamma(i) \lambda_{i,t-1} + \nu_{i,t} \quad \nu_{i,t} \sim \mathcal{N}(0, \phi_i)
\]  

(4)
Time Varying Parameters

Some background

\[
y_t = A_{1,t}y_{t-1} + A_{2,t}y_{t-2} + \ldots + A_{p,t}y_{t-p} + Cx_t + \varepsilon_t
\] (5)

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

\[
\beta_t = \beta_{t-1} + \nu_t, \quad \nu_t \sim \mathcal{N}(0, \Omega)
\] (6)

\[
\varepsilon_t \sim \mathcal{N}(0, \Sigma_t)
\] (7)

\[
\Sigma_t = F\Lambda_tF'
\] (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, \ldots, T \quad (9) \\

This model may rewrite as:

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

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

\[ y_t = A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + C x_t + \varepsilon_t \]  

(13)

\[ \varepsilon_t \sim \mathcal{N}(0, \Sigma) \]  

(14)

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

\[ \Delta y_t = \Pi y_{t-1} + \Lambda_1 \Delta y_{t-1} + \ldots + \Lambda_{p-1} \Delta y_{t-p} + C x_t + \varepsilon_t \]  

(15)

where \( \Pi = (A_1 + \ldots + A_p) - I_n \) and \( \lambda_j = -(A_{j+1} \ldots) + A_p \), with \( j = 1, \ldots, p - 1 \).

Prior for \( \Pi \):

\[ \Delta y_t = \Gamma \tilde{y}_{t-1} + \Lambda_1 \Delta y_{t-1} + \ldots + \Lambda_{p-1} \Delta y_{t-p} + C x_t + \varepsilon_t \]  

(16)

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

\[ \Gamma_i | H_i, \Sigma \sim \mathcal{N} \left( 0, \lambda_8 (H_i) \Sigma \right) \]  

(17)