# BEAR 5.1

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https://github.com/european-central-bank/BEAR-toolbox

# BEAR 5.1: what's new?

1. BEAR Infrastructure upgraded
   - Facilitate running multiple estimations simultaneously
   - Allow working in arbitrary folders
2. BEAR inputs are now objects to enable easy adjustments
   - Provide a set of default values on each property
   - Easier tracking of models
3. Created a new modern interface
   - Works with the new BEAR settings objects
   - Provide easy-to-discover examples that help the users get started
4. Moved BEAR to a source control system
   - Facilitate development and testing
   - Easier for the community to provide feedback

# BEAR 5.0: features

1. Factor-augmented VARs, Bernanke et al. (2005)
2. (Bayesian) Proxy SVARs, Caldara and Herbst (2019)
3. Trend-cycle VARs, Banbura and Van Vlodrop (2019)
4. Mixed Frequency Bayesian VARs, Schorfheide and Song (2015)
5. New identification techniques

# BEAR 5 quotes

### Gary Koop, Professor University Strathclyde

- Bayesian VAR analysis is made easy using the BEAR toolbox. It is a powerful tool for academics, central bankers and policymakers.

### Fabio Canova, Professor Norwegian Business School

- A toolbox built by policymakers for policymakers. A must!

### Giorgio E Primiceri, Professor Northwestern

- BEAR is an invaluable, user-friendly toolbox for the Bayesian estimation of state-of-the-art multivariate time-series models. Not only it is accessible to less-technical users, but also extremely useful to more advanced researchers.

# Outline

# Short recap of BEAR

BEAR is a comprehensive (Bayesian) VAR toolbox for Research and Policy analysis.

Aim to satisfy 3 main objectives:

1. Easy to understand, augment and adapt. 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 4

## 5 estimation types of VAR models

1. Standard OLS VAR
2. Bayesian VAR: many prior distributions
3. Mean-adjusted Bayesian VAR
4. Panel VAR: 6 types
5. Time Varying Parameters & Stochastic Volatility

## Identifications and applications

- Sign and magnitude restrictions
- Conditional forecasts
- Historical decompositions and FEVD

# Factor Augmented VARs

## Motivation

- "... small number of variables is unlikely to span the information sets used by actual central banks, which are known to follow literally hundreds of data series..." Bernanke et al. 2005
- Extract factors from (very) large "information" data sets

## Pro

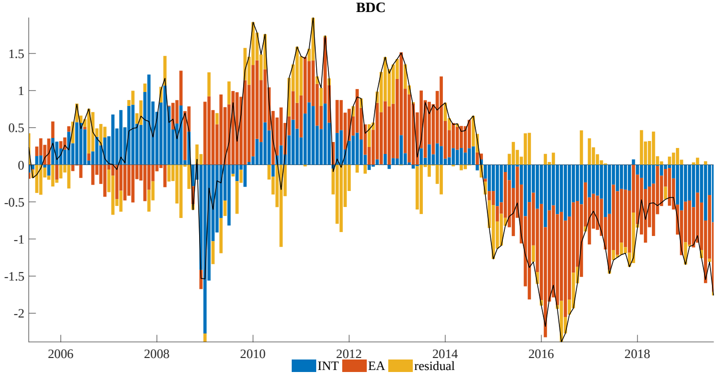
- Few factors summarise a large amount of information
- Better representation of economic concepts (e.g. price pressure, trade tensions, uncertainty)

## Con

- Factors are hard to interpret

# Factor Augmented VARs

## Example output: What is driving long-term inflation expectations?



# (Bayesian) Proxy SVARs

## Motivation

- "... the instrument is constructed as a partial measure of the shock of interest: [...] the part of a monetary shock revealed during a monetary policy announcement window." Stock & Watson (2018)
- Identifies the shock based on covariance restrictions with a suitable proxy variable.

## Pro

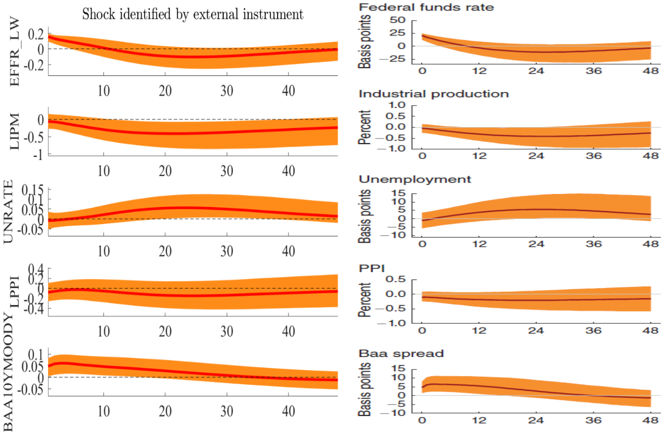
- Identifies the shock without imposing any theoretical structure
- Avoids drawbacks of conventional identification schemes
- Combination with sign/magnitude restrictions

## Con

- Limited amount of suitable proxy variables

# (Bayesian) Proxy SVARs

## Example output: Replication of Caldara and Herbst (2019)



# Trend-Cycle Bayesian VARs

## Motivation

- "The slowly changing mean can account for a number of secular developments such as changing inflation expectations, slowing productivity growth or demographics." Banbura, Van Vlodrop (2018)
- time-varying unconditional mean is anchored to off-model information, i.e. survey forecasts

## Pro

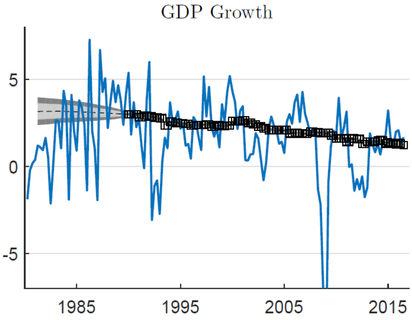
- Increased forecasting performance by reducing uncertainty about the uncond. mean

## Con

- Suitable survey forecast not available for all variables of interest

# Trend-Cycle Bayesian VARs

## Example output Banbura and Van Vlodrop (2018)



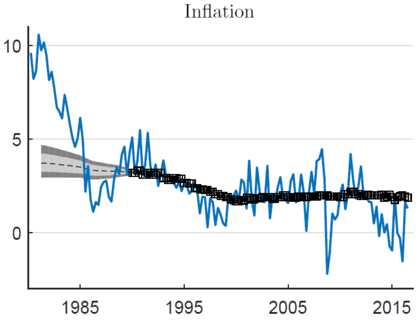




Figure 1: Posterior distributions for the end-of-sample local and unconditional means

# Mixed-Frequency Bayesian VARs

## Motivation

- "Modern Big Data analytics, often referred to as the three “Vs”: the large number of time series continuously released (Volume), the complexity of the data covering various sectors of the economy, published in an asynchronous way and with different frequencies and precision (Variety), and the need to incorporate new information within minutes of their release (Velocity). ... BVARs are able to effectively handle the three Vs ...", (Cimadomo et al. 2020).

## Pro

- Flexible to use big data in real time for nowcasting

## Con

- Computationally intensive

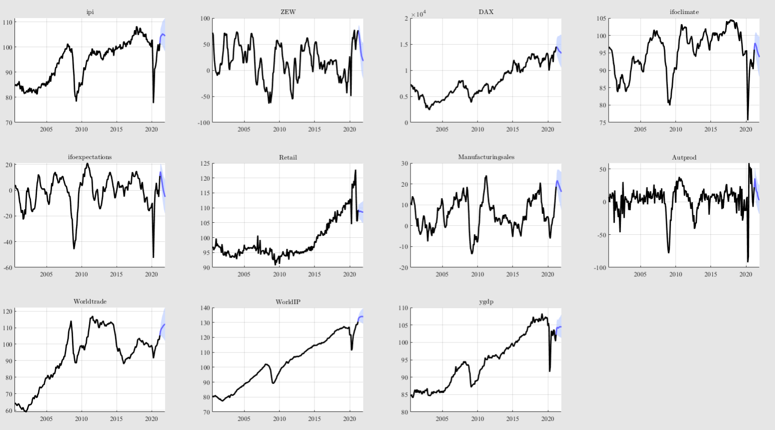



Figure 2: Nowcasting German GDP with a MF Bayesian VAR

# BEAR 5.0 More features

## More identification approaches

### Long run zero restrictions (Blanchard and Quah 1989)

- In BEAR, enter '1000 1000' in the periods for the zero restrictions

### Correlation restrictions (Ludvigson et al. 2017)

- In BEAR, enter the external variable in the sheet 'IV' and specify the name of the shock to be correlated.

### Relative magnitude restrictions (Caldara et al. 2016)

- In BEAR, enter S1 for stronger and W1 for weaker in sheet 'relmagn res value'.

### FEVD restrictions (Weale and Wieladek 2016)

- In BEAR, enter .Absolute or .Relative in sheet 'FEVD res value'.

## Variable specific priors for the AR coefficient

- In BEAR, enter the values in sheet 'AR priors' and select in interface.

## Priors for exogenous variables

- In BEAR, enter the prior value in sheet 'exo priors' and select in interface.

# BEAR 5.0 More features

Moved to Github and has replications

## BEAR 5.0 is open source

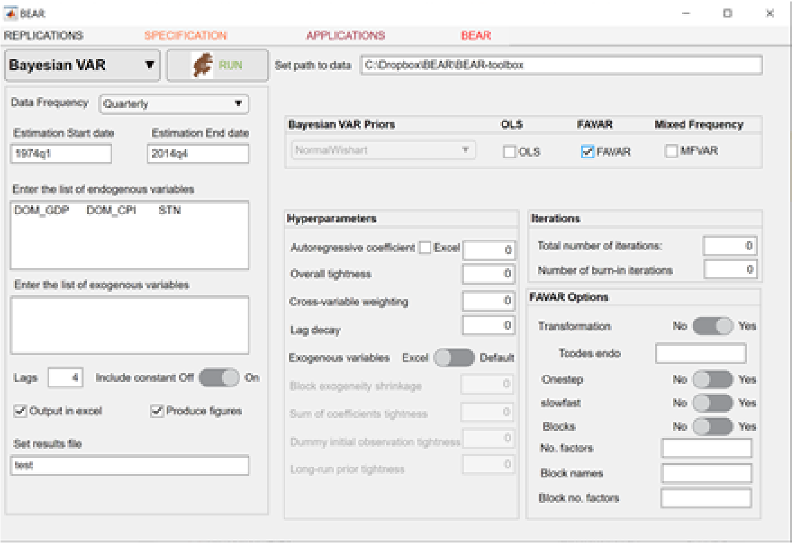
- BEAR will be regularly updated on Github: https://github.com/european-central-bank/BEAR-toolbox
- Also available from ECB website: https://www.ecb.europa.eu/pub/research/working-papers/html/bear-toolbox.en.html

## BEAR 5.0 has 5 replication files

- Banbura and van Vlodrop (2018)
- Caldara and Herbst (2019)
- Amir-Ahmadi and Uhlig (2015)
- Bernanke, Boivin and Eliasz (2004)
- Wieladek and Garcia Pascual (2016)

# BEAR 5.0 More features

## New interface

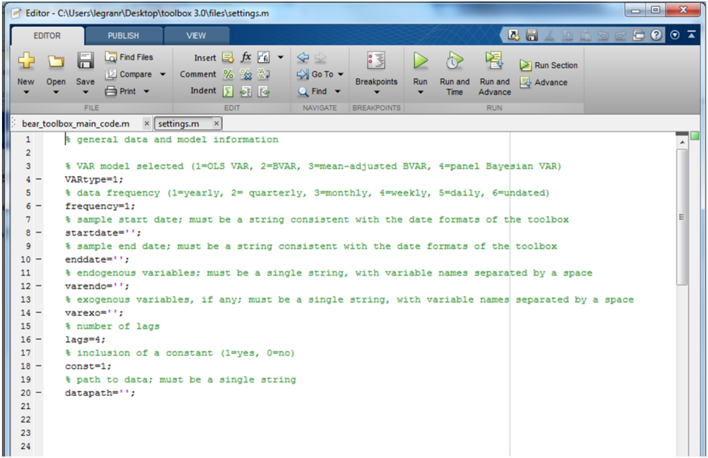


# BEAR 4 Recap

- Developers version
- Stochastic Volatility
- Time Varying Parameters
- Forecast evaluation

# Developer's version

- Less restrictive than the interface for potential customised use
- Example: implementation of automatic loop



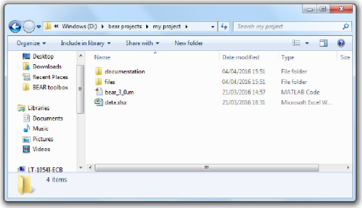
# User and Technical guide



guide providing the mathematical derivations for the models and applications implemented by the toolbox.
- the 'files' folder. This folder contains the set of matlab functions run by the code. Except in a few specific cases indicated in this guide, you should not alter nor delete any elements in this folder. Doing so may result in the code not working properly anymore.
- the 'bear_3_0.m' matlab file. This file is used to start the toolbox and run the estimation. Further details can be found in chapter 3: Running your project.
- the 'data.xlsx' Excel file. This file contains the data that will be used by the toolbox to run the estimation.

By default, the toolbox folder is called 'bear toolbox 3.0'. However, it is possible to rename the folder to suit your particular project, for instance 'project Japan', or 'BVAR US'. You may then place the folder in any directory of your choice. For example, you may create a new project, and for this project change the folder name from 'bear toolbox 3.0' to 'my project'. Assume that for convenience you also create a new folder on your D drive called 'bear projects' that gathers all your different projects. You may then move 'my project' into 'bear projects'. Your project folder will then look as follows:

**Figure 2.2.:** *Project folder*








## A.3. Derivations of the posterior distribution with a Minnesota prior

The derivation of the posterior distribution with a Minnesota prior remains relatively simple. It starts with equation 1.3.15:

$$\pi(\beta\,|y) \propto \exp\left[-\frac{1}{2}\left\{\left(y-\bar{X}\beta\right)'\bar{\Sigma}^{-1}\left(y-\bar{X}\beta\right)+(\beta-\beta_0)'\Omega_0^{-1}(\beta-\beta_0)\right\}\right] \tag{A.3.1}$$

To transform this expression, consider only the exponential part in the curly brackets and develop it:

$$\begin{aligned}&\left(y-\bar{X}\beta\right)'\bar{\Sigma}^{-1}\left(y-\bar{X}\beta\right)+(\beta-\beta_0)'\Omega_0^{-1}(\beta-\beta_0)\\&=y'\bar{\Sigma}^{-1}y+\beta'\bar{X}'\bar{\Sigma}^{-1}\bar{X}\beta-2\beta'\bar{X}'\bar{\Sigma}^{-1}y+\beta'\Omega_0^{-1}\beta+\beta_0'\Omega_0^{-1}\beta_0-2\beta'\left(\Omega_0^{-1}\right)'\beta_0\\&=y'\bar{\Sigma}^{-1}y+\beta'\left(\Omega_0^{-1}+\bar{X}'\bar{\Sigma}^{-1}\bar{X}\right)\beta-2\beta'\left(\Omega_0^{-1}\beta_0+\bar{X}'\bar{\Sigma}^{-1}y\right)+\beta_0'\Omega_0^{-1}\beta_0\end{aligned} \tag{A.3.2}$$

Notice that A.3.1 resembles the kernel of a normal distribution, but with a sum of squares rather than a single square term within the exponential part. It would therefore be nice to replace this sum by a single square, to obtain the kernel of a normal distribution. This can be done by applying the manipulations known as "completing the square". This most of the time amounts to adding and subtracting an additional matrix term, and inserting the product of a matrix with its inverse. After factoring, this will eventually lead to a single squared form, while the additional terms created will be independent of $\beta$ and will hence be relegated to the proportionality constant. Hence, complete the squares in A.3.2):

$$=y'\bar{\Sigma}^{-1}y+\beta'\left(\Omega_0^{-1}+\bar{X}'\bar{\Sigma}^{-1}\bar{X}\right)\beta-2\beta'\bar{\Omega}^{-1}\bar{\Omega}\left(\Omega_0^{-1}\beta_0+\bar{X}'\bar{\Sigma}^{-1}y\right)+\beta_0'\Omega_0^{-1}\beta_0+\bar{\beta}'\bar{\Omega}^{-1}\bar{\beta}-\bar{\beta}'\bar{\Omega}^{-1}\bar{\beta} \tag{A.3.3}$$

Note that A.3.3 holds whatever the definition of $\bar{\Omega}$ and $\bar{\beta}$ (as long as dimensions agree). Nevertheless, one may obtain the desired squared form from A.3.3 by defining:

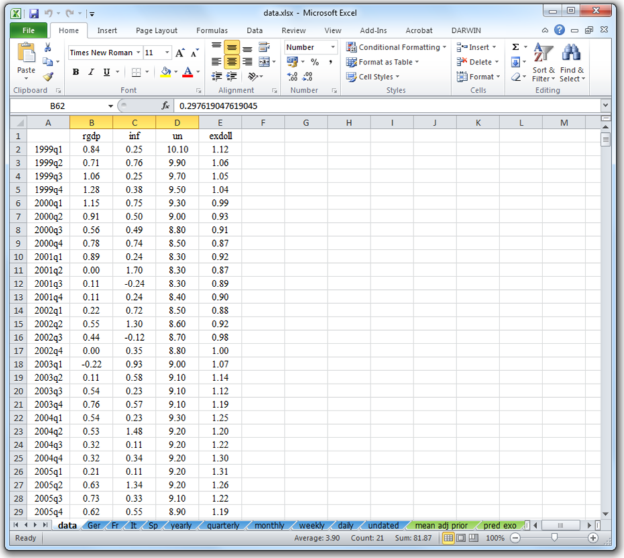
$$\bar{\Omega}=\left(\Omega_0^{-1}+\bar{X}'\bar{\Sigma}^{-1}\bar{X}\right)^{-1}$$

$$\text{and} \tag{A.3.4}$$

$$\bar{\beta}=\bar{\Omega}\left(\Omega_0^{-1}\beta_0+\bar{X}'\bar{\Sigma}^{-1}y\right) \tag{A.3.5}$$

For then, A.3.3 rewrites:

# Input: Excel data file




| | rgdp | inf | un | exdoll |
|---|---|---|---|---|
| 1999q1 | 0.84 | 0.25 | 10.10 | 1.12 |
| 1999q2 | 0.71 | 0.76 | 9.90 | 1.06 |
| 1999q3 | 1.06 | 0.25 | 9.70 | 1.05 |
| 1999q4 | 1.28 | 0.38 | 9.50 | 1.04 |
| 2000q1 | 1.15 | 0.75 | 9.30 | 0.99 |
| 2000q2 | 0.91 | 0.50 | 9.00 | 0.93 |
| 2000q3 | 0.56 | 0.49 | 8.80 | 0.91 |
| 2000q4 | 0.78 | 0.74 | 8.50 | 0.87 |
| 2001q1 | 0.89 | 0.24 | 8.30 | 0.92 |
| 2001q2 | 0.00 | 1.70 | 8.30 | 0.87 |
| 2001q3 | 0.11 | -0.24 | 8.30 | 0.89 |
| 2001q4 | 0.11 | 0.24 | 8.40 | 0.90 |
| 2002q1 | 0.22 | 0.72 | 8.50 | 0.88 |
| 2002q2 | 0.55 | 1.30 | 8.60 | 0.92 |
| 2002q3 | 0.44 | -0.12 | 8.70 | 0.98 |
| 2002q4 | 0.00 | 0.35 | 8.80 | 1.00 |
| 2003q1 | -0.22 | 0.93 | 9.00 | 1.07 |
| 2003q2 | 0.11 | 0.58 | 9.10 | 1.14 |
| 2003q3 | 0.54 | 0.23 | 9.10 | 1.12 |
| 2003q4 | 0.76 | 0.57 | 9.10 | 1.19 |
| 2004q1 | 0.54 | 0.23 | 9.30 | 1.25 |
| 2004q2 | 0.53 | 1.48 | 9.20 | 1.20 |
| 2004q3 | 0.32 | 0.11 | 9.20 | 1.22 |
| 2004q4 | 0.32 | 0.34 | 9.20 | 1.30 |
| 2005q1 | 0.21 | 0.11 | 9.20 | 1.31 |
| 2005q2 | 0.63 | 1.34 | 9.20 | 1.26 |
| 2005q3 | 0.73 | 0.33 | 9.10 | 1.22 |
| 2005q4 | 0.62 | 0.55 | 8.90 | 1.19 |

## Motivation

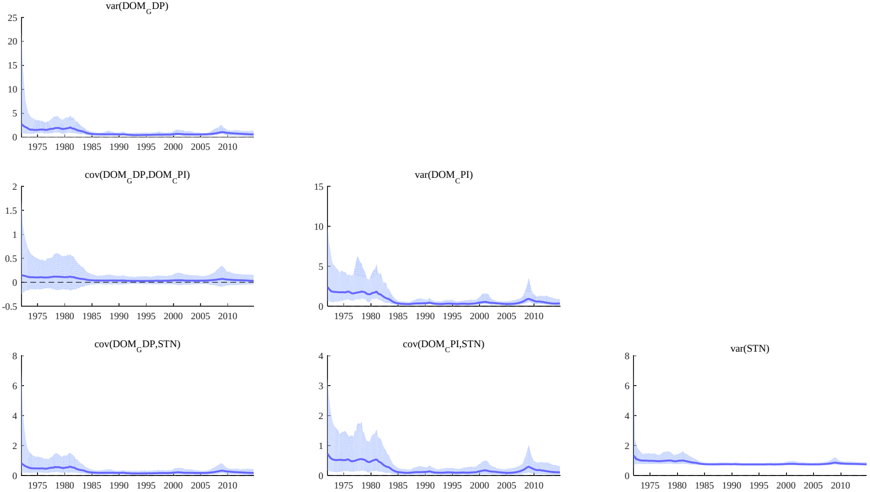
- A data-generating process of economic variables often seems to have drifting coefficients and shocks of stochastic volatility.
- In particular, VAR innovation variances change over time (Bernanke and Mihov 1998, Kim and Nelson 1999, MacConnell and Perez Quiros 2000).

## 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

## Example output



# Time Varying Parameters

## Motivation and setup in BEAR

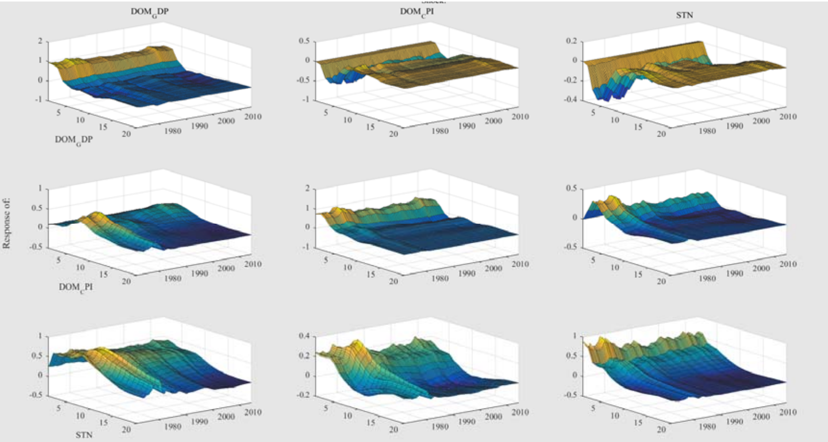
### Motivation

- "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?

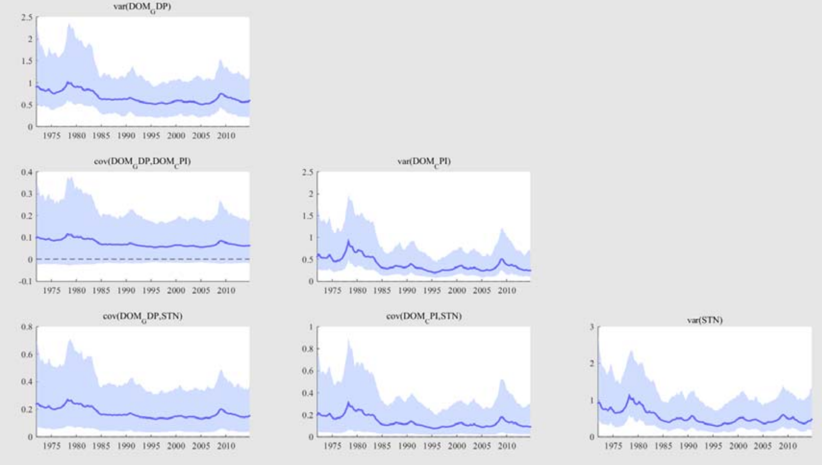
### Set-up in BEAR

- 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
## Example output



# Time Varying Parameters
## Example output



# Equilibrium VARs

## Motivation and setup in BEAR

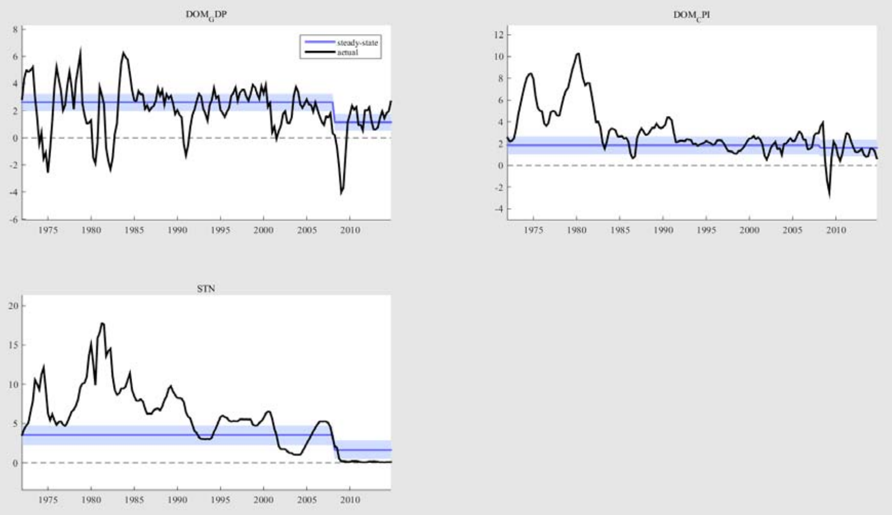
### Motivation

- 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
## Example output



# Priors for the long-run

## Motivation and setup in BEAR

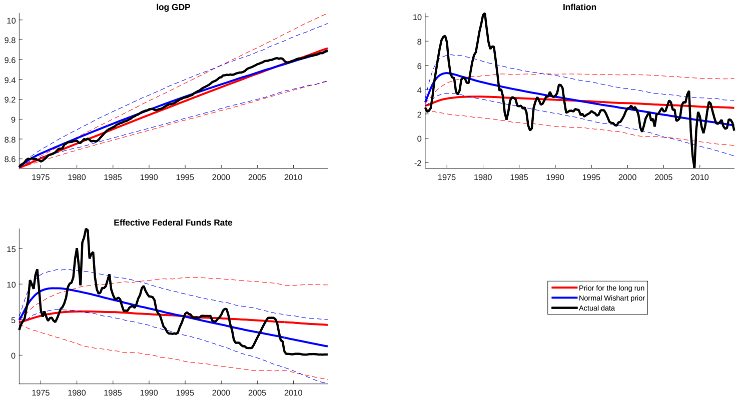
### Motivation

- 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
## Example output



# Forecasting evaluation procedures

Motivation and setup in BEAR

## Motivation

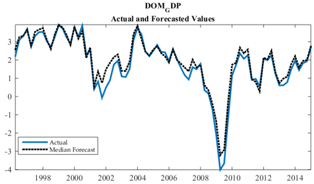
- Assess forecasting performance of our VAR.
- Large literature has provided important insights on how to test whether forecasts are optimal / rational.
- Traditional tests that are based on stationarity assumptions should not be used in the presence of instabilities.

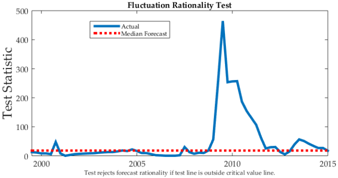
## Set-up in BEAR

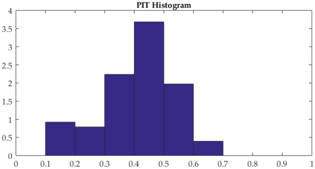
- Rossi and Sekhposyan (2016, 2017) and Loria and Rossi (2017).
- Rolling window estimations with density and forecast evaluation.

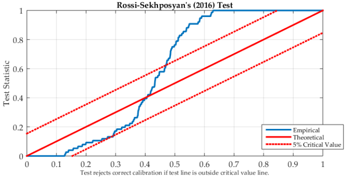
# Forecasting evaluation procedures

## Example Output



# 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)