

Framework

Consider the Normal-Inverse-Wishart (NIW) prior for the pair $(\mathbf{B}, \mathbf{\Sigma})$, where:

$$\mathbf{\Sigma} \sim \mathcal{IW}_n(\nu, \mathbf{\Phi})$$

and

$$\mathbf{B} \mid \mathbf{\Sigma} \sim \mathcal{MN}_{n \times m}(\mathbf{\Psi}, \mathbf{\Omega}, \mathbf{\Sigma})$$

where the density of the Inverse Wishart is:

$$\mathcal{IW}_n(\mathbf{\Sigma}; \nu, \mathbf{\Phi}) \propto |\mathbf{\Sigma}|^{-(\nu+n+1)/2} \exp\left(-\frac{1}{2} \text{tr}(\mathbf{\Phi} \mathbf{\Sigma}^{-1})\right)$$

and the density of \mathbf{B} conditional on $\mathbf{\Sigma}$ is:

$$\begin{aligned} \mathcal{MN}_{n \times m}(\mathbf{B}; \mathbf{\Psi}, \mathbf{\Omega}, \mathbf{\Sigma}) &\propto |\mathbf{\Sigma}|^{-m/2} \exp\left(-\frac{1}{2} \text{vec}(\mathbf{B} - \mathbf{\Psi})^\top (\mathbf{\Sigma} \otimes \mathbf{\Omega})^{-1} \text{vec}(\mathbf{B} - \mathbf{\Psi})\right) \\ &= |\mathbf{\Sigma}|^{-m/2} \exp\left(-\frac{1}{2} \text{tr}\left[(\mathbf{B} - \mathbf{\Psi})^\top \mathbf{\Omega}^{-1} (\mathbf{B} - \mathbf{\Psi}) \mathbf{\Sigma}^{-1}\right]\right) \\ &= |\mathbf{\Sigma}|^{-m/2} \exp\left(-\frac{1}{2} \text{tr}\left[\mathbf{\Omega}^{-1} (\mathbf{B} - \mathbf{\Psi})^\top \mathbf{\Sigma}^{-1} (\mathbf{B} - \mathbf{\Psi})\right]\right) \end{aligned}$$

“Weak” Normal-Inverse-Wishart Prior

Also known as Uligh or Jeffrey Prior

We specify the following parameters:

$$\begin{aligned} \nu &= 0 \\ \mathbf{\Phi} &= \mathbf{0}_{n \times n} \\ \mathbf{\Psi} &= \mathbf{0}_{n \times m} \\ \mathbf{\Omega}^{-1} &= \mathbf{0}_{m \times m} \quad \Rightarrow \quad \mathbf{\Omega} = \text{diag}(\infty, \dots, \infty) \end{aligned}$$

The joint prior density reduces to:

$$\pi(\mathbf{B}, \mathbf{\Sigma}) \propto |\mathbf{\Sigma}|^{-(\nu+n+1)/2} = |\mathbf{\Sigma}|^{-(n+1)/2}$$

Uniform Prior on join Impulse Responses

Given the parameterization:

$$\begin{aligned} \nu &= -(m-3) - (n+1) \\ \mathbf{\Phi} &= \mathbf{0}_{n \times n} \\ \mathbf{\Psi} &= \mathbf{0}_{n \times m} \\ \mathbf{\Omega}^{-1} &= \mathbf{0}_{m \times m} \quad \Rightarrow \quad \mathbf{\Omega} = \text{diag}(\infty, \dots, \infty) \end{aligned}$$

the implied prior over $(\mathbf{B}, \mathbf{\Sigma})$ is:

$$\pi(\mathbf{B}, \mathbf{\Sigma}) \propto |\mathbf{\Sigma}|^{-(\nu+n+1)/2} = |\mathbf{\Sigma}|^{(m-3)/2}$$

Minnesota Prior

$$\begin{aligned}\nu &= n + 2 \\ \Phi &= \text{diag}(\phi_1, \dots, \phi_n), \text{ where } \phi_i = \hat{\sigma}_i^2(\nu - n - 1) \\ \Psi &= (\Psi)_{ij} = \begin{cases} 1 & \text{if } i = j \text{ and } i = \{1, \dots, n\} \\ 0 & \text{otherwise} \end{cases} \\ \Omega &= \begin{bmatrix} \tilde{\Omega} & \mathbf{0} \\ \mathbf{0} & V_c \end{bmatrix}, \quad \tilde{\Omega} = \mathbf{K} \otimes \Phi^{-1}\end{aligned}$$

with $\mathbf{K} = \text{diag}\left(\frac{(\nu-n-1)\lambda_1^2}{1^{\lambda_3}}, \dots, \frac{(\nu-n-1)\lambda_n^2}{p^{\lambda_3}}\right)$ and where $\hat{\sigma}_i^2$ is the residual variance from fitting an AR(p) to variable i . This is related to the fact that

$$\mathbb{E}(\Sigma) = \Phi/(\nu - n - 1) \text{ hence } \mathbb{E}(\Sigma) = \text{diag}(\hat{\sigma}_1^2, \dots, \hat{\sigma}_n^2).$$

Minnesota Prior with Dummy Observations

The Minnesota prior with dummy observations combines T^* dummy observations, whose likelihood is

$$p(\mathbf{Y}^* | \mathbf{B}, \Sigma),$$

where \mathbf{Y}^* is a $T \times n$ matrix, with a prior with the following parameters

$$\begin{aligned}\nu &= 2 \\ \Phi &= \mathbf{0}_{n \times n} \\ \Psi &= \mathbf{0}_{n \times m} \\ \Omega^{-1} &= \mathbf{0}_{m \times m} \quad \Rightarrow \quad \Omega = \text{diag}(\infty, \dots, \infty)\end{aligned}$$

Del Negro and Schorfheide's (2010) Handbook Chapter use a prior over (\mathbf{B}, Σ) that is proportional to the prior $|\Sigma|^{-(n+1)/2}$. We use a different one to guarantee equality with the implementation of the Minnesota prior described above.

The dummy observations are as follows:

$$\mathbf{Y}^* = \mathbf{X}^* \mathbf{B} + \mathbf{U}$$

$$\mathbf{Y}^* = \begin{bmatrix} \mathbf{y}_1^{*'} \\ \vdots \\ \mathbf{y}_{T^*}^{*'} \end{bmatrix}, \quad \mathbf{X}^* = \begin{bmatrix} \mathbf{x}_1^{*'} \\ \vdots \\ \mathbf{x}_{T^*}^{*'} \end{bmatrix}, \quad \mathbf{x}_t^{*'} = [\mathbf{y}_{t-1}^{*'}, \dots, \mathbf{y}_{t-p}^{*'}, 1], \quad \mathbf{U} = \begin{bmatrix} \mathbf{u}_1^{*'} \\ \vdots \\ \mathbf{u}_{T^*}^{*'} \end{bmatrix}$$

where $\mathbf{B} = [\mathbf{B}'_1, \dots, \mathbf{B}'_p, \mathbf{c}']'$.

Illustration with 2 variables and 2 lags Based on Del Negro and Schorfheide's (2010) handbook chapter. The prior for \mathbf{B}_1 is implemented via

$$\begin{bmatrix} \frac{\sqrt{\phi_1}}{\lambda_1} & 0 \\ 0 & \frac{\sqrt{\phi_2}}{\lambda_1} \end{bmatrix} = \begin{bmatrix} \frac{\sqrt{\phi_1}}{\lambda_1} & 0 & 0 & 0 & 0 \\ 0 & \frac{\sqrt{\phi_2}}{\lambda_1} & 0 & 0 & 0 \end{bmatrix} \mathbf{B}_1 + \begin{bmatrix} u_{11} & u_{12} \\ u_{21} & u_{22} \end{bmatrix}$$

The prior for \mathbf{B}_2 is implemented via

$$\begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 0 & \frac{\sqrt{\phi_1}}{\lambda_1} 2^{\frac{\lambda_3}{2}} & 0 & 0 \\ 0 & 0 & 0 & \frac{\sqrt{\phi_2}}{\lambda_1} 2^{\frac{\lambda_3}{2}} & 0 \end{bmatrix} \mathbf{B}_2 + \mathbf{U},$$

Then, the combination of the likelihood of the dummy observations and the weak prior yields:

$$\begin{aligned} \boldsymbol{\Sigma} &\sim \mathcal{IW}_n(\nu, \boldsymbol{\Phi}) \\ \mathbf{B} \mid \boldsymbol{\Sigma} &\sim \mathcal{MN}_{n \times m}(\mathbf{B}; \boldsymbol{\Psi}, \boldsymbol{\Omega}, \boldsymbol{\Sigma}) \end{aligned}$$

where:

$$\begin{aligned} \nu &= n + 2 \\ \boldsymbol{\Omega} &= (\mathbf{X}^{*'} \mathbf{X}^*)^{-1} \\ \boldsymbol{\Psi} &= \boldsymbol{\Omega}(\mathbf{X}^{*'} \mathbf{Y}^*) \\ \boldsymbol{\Phi} &= \mathbf{Y}^{*'} \mathbf{Y}^{*'} - \boldsymbol{\Psi}' \boldsymbol{\Omega}^{-1} \boldsymbol{\Psi} \end{aligned}$$

References

Del Negro, M. and F. Schorfheide (2010). Bayesian Macroeconometrics. In *The Oxford Handbook of Bayesian Econometrics*.