Online Appendix A: VB for the first-stage estimations

1 The Model

The model below is model (4) in the main paper. For notational simplicity, we suppress the subscripts that indicate the model is related to the i^{th} equation of the panel SAR model.

$$Y = X\Upsilon + E,\tag{1}$$

where $vec(E) \sim N(0, \Sigma_E \otimes I_T)$. The dimensions of Y and the standardized regressors X are $T \times n$ and $T \times p$, respectively, and Υ is of dimension $p \times n$.

Let S = E'E and $\Omega = \Sigma_E^{-1}$, the likelihood in equation (1) can be expressed as

$$L(\Omega) \propto |\Omega|^{\frac{T}{2}} exp\{-\frac{1}{2}tr(S\Omega)\}.$$
 (2)

2 The Priors

2.1 The Priors of Υ

Let $\gamma = vec(\Upsilon)$. Following Bhattacharya, Pati, Pillai, and Dunson (2015), we set hierarchical D-L prior for the j^{th} (j = 1, ..., np) element of γ as follows:

$$\gamma_j | \phi, \tau \sim DE(\phi_j \tau), \quad \phi_j \sim Dir(a, ..., a).$$
 (3)

Conditional prior for γ_j is $DE(\phi_j\tau)$ implies a zero mean Double Exponential or Lapalace distribution with the density $f(\gamma_j) = (2\phi_j\tau)^{-1} exp(-\frac{|\gamma_j|}{\phi_j\tau})$ for $\gamma_j \in \mathbb{R}$.

Next, we set a Gamma prior for τ :

$$\tau \sim G(npa, 1/2). \tag{4}$$

The above hierarchical D-L prior for γ_j can be expressed as:

$$\gamma_j \sim N(0, \psi_j \phi_j^2 \tau^2), \quad \psi_j \sim Exp(1/2).$$
 (5)

Hence, the prior of γ is $N(\mathbf{0}, \underline{V})$, where $\underline{V} = diag(\psi_1 \phi_1^2 \tau^2, ..., \psi_{np} \phi_{np}^2 \tau^2)$.

2.2 The Priors of Ω

We set Exponential priors and D-L priors for the elements of Ω as follows:

$$\omega_{ii} \sim Exp(\underline{s}), \quad i = 1, ..., n$$

$$\omega_{ij} \sim N(0, \psi_{\omega,ij} \phi_{\omega,ij}^2 \tau_{\omega}^2), \quad \psi_{\omega,ij} \sim Exp(1/2), \quad i < j = 2,, n$$

$$\phi_{\omega,ij} \sim Dir(a_{\omega},, a_{\omega}), \quad \tau_{\omega} \sim G(\frac{n^2 - n}{2} a_{\omega}, 1/2)$$
(6)

where with a slight abuse of notations, we use ω_{ii} and ω_{ij} to denote the diagonal and off-diagonal elements of Ω .

3 The Posteriors

3.1 The Posteriors of B and its related hyperparameters

The conditional posterior of γ is $N(\tilde{\gamma}, \tilde{V})$, where $\tilde{V} = (\underline{V}^{-1} + \Omega \otimes (X'X))^{-1}$, and $\tilde{\gamma} = \tilde{V}(\Omega \otimes X')vec(Y)$.

The conditional posterior of τ is $giG(npa-np, 1, \sum_{j=1}^{np} \frac{2|\gamma_j|}{\phi_j})$.

The conditional posterior of ϕ_j can be derived as following: First, we have $\xi_j \sim giG(a-1,1,2|\gamma_j|)$. Next let et $\Xi = \sum_{j=1}^{np} \xi_j$. The conditional posterior of ϕ_j can then be found to be ξ_j/Ξ .

The conditional posterior of $1/\psi_j$ is Inverse Gaussian with mean $\sqrt{\frac{\phi_j^2\tau^2}{\gamma_j^2}}$ and scale parameter 1.

3.2 The Posteriors of Ω and its related hyperparameters

Following Wang (2012), we focus on the last column and row of Ω then use Block Gibbs sampler to update the relevant parameters and hyperparameters.

Let H be the $n \times n$ matrix with 0 diagonal elements and the off diagonal element at i^{th} row and j^{th} column be $\psi_{\omega,ij}\phi_{\omega,ij}^2\tau_{\omega}^2$. Partition Ω , S and H as follows:

$$\Omega = \begin{pmatrix} \Omega_{-n,-n} & \omega_{-n,n} \\ \omega'_{-n,n} & \omega_{nn} \end{pmatrix} S = \begin{pmatrix} S_{-n,-n} & s_{-n,n} \\ s'_{-n,n} & s_{nn} \end{pmatrix} H = \begin{pmatrix} H_{-n,-n} & h_{-n,n} \\ h'_{-n,n} & h_{nn} \end{pmatrix}$$
(7)

 $^{^{1}}y \sim giG(p, a, b) \text{ if } f(y) \propto y^{p-1}exp[-\frac{1}{2}(ay + b/y)].$

where -n denotes the set of all indices except for n.

Let $b_1 = \omega_{n,n} - \omega'_{-n,n} \Omega^{-1}_{-n,-n} \omega_{-n,n}$ and $b_2 = \omega_{-n,n}$. The conditional posteriors are as follows:

$$b_{1} \sim G(\frac{T}{2} + 1, \frac{s_{nn} + \underline{s}}{2})$$

$$b_{2} \sim N(-C\mathbf{s}_{-n,n}, C), \quad C = ((\underline{s} + s_{nn})\Omega_{-n,-n}^{-1} + H^{*-1})^{-1}, \quad H^{*} = diag(h_{-n,n})$$

$$1/\psi_{\omega,ij} \sim iG(\sqrt{\frac{\tau_{\omega}^{2}\phi_{\omega,ij}^{2}}{\omega_{ij}^{2}}}, 1)$$

$$\tau_{\omega} \sim giG(\frac{n^{2} - n}{2}(a_{3} - 1), 1, \sum_{i < j} \frac{2|\omega_{ij}|}{\phi_{\omega,ij}})$$

$$\xi_{\omega,ij} \sim giG(a_{\omega} - 1, 1, 2|\omega_{ij}|), \quad \phi_{\omega,ij} = \xi_{\omega,ij} / \sum_{i < j} \xi_{\omega,ij}$$
(8)

4 Optimal VB q densities

4.1 $q(\gamma)$

$$q(\gamma) \sim N(\bar{\gamma}, \overline{V}),$$
 (9)

where

$$\overline{V} = (V^{-1} + \overline{\Omega} \otimes (X'X))^{-1},$$
$$\overline{\gamma} = \overline{V}(\overline{\Omega} \otimes X')vec(Y),$$

and

$$V^{-1} = diag(\frac{1}{\psi_1} \frac{1}{\phi_1^2} \frac{1}{\tau^2}, ..., \frac{1}{\psi_{np}} \frac{1}{\phi_{np}^2} \frac{1}{\tau^2}).$$

4.2 $q(\tau)$

$$q(\tau) \sim giG[npa - np, 1, \sum_{j=1}^{np} 2(\overline{\gamma}_j^2 + \overline{V}_{jj})^{1/2} \frac{1}{\overline{\phi_j}}]$$
 (10)

Let $\chi = \sum_{j=1}^{np} 2(\overline{b}_j^2 + \overline{V}_{jj})^{1/2} \frac{1}{\overline{\phi}_j}$. We have

$$\bar{\tau} = \frac{\sqrt{\chi} K_{npa-np+1}(\sqrt{\chi})}{K_{npa-np}(\sqrt{\chi})},$$

and

$$\overline{\tau^2} = \overline{\tau}^2 + \chi \left[\frac{K_{npa-np+2}(\sqrt{\chi})}{K_{npa-np}(\sqrt{\chi})} - \left(\frac{K_{npa-np+1}(\sqrt{\chi})}{K_{npa-np}(\sqrt{\chi})} \right)^2 \right],$$

where $K_*[ullet]$ is the modified Bessel functions of the second kind.

4.3 $q(\psi_i)$

$$q(\psi_j^{-1}) \sim iG(\sqrt{\frac{\overline{\phi_j^2} \, \overline{\tau^2}}{\overline{\gamma_j^2} + \overline{V}_{jj}}}, 1), \tag{11}$$

Let
$$\rho = \sqrt{\frac{\overline{\phi_j^2} \, \overline{\tau^2}}{\overline{\gamma_j^2} + \overline{V}_{jj}}}$$
.

$$\overline{\psi_j^{-1}} = \rho,$$

and

$$\overline{\psi}_j = 1 + 1/\rho.$$

4.4 $q(\phi_i)$

$$q(\xi_j) \sim giG(a-1, 1, 2\sqrt{\overline{\gamma}_j^2 + \overline{V}_{jj}})$$
 (12)

Let $\varpi = 2\sqrt{\overline{\gamma}_j^2 + \overline{V}_{jj}}$. We have

$$\overline{\xi_j} = \frac{\sqrt{\overline{\omega}} K_a(\sqrt{\overline{\omega}})}{K_{a-1}(\sqrt{\overline{\omega}})},$$

and

$$var(\xi_j) = \varpi \left\{ \frac{K_{a+1}(\sqrt{\varpi})}{K_{a-1}(\sqrt{\varpi})} - \left[\frac{K_a(\sqrt{\varpi})}{K_{a-1}(\sqrt{\varpi})} \right]^2 \right\},\,$$

where $var(\bullet)$ denotes the variance.

Scaling ξ_i , we have

$$\overline{\phi_j} = \frac{\overline{\xi_j}}{\sum_{j=1}^{np} \overline{\xi_j}},$$

and

$$\overline{\phi_j^2} = \overline{\phi_j}^2 + \frac{var(\xi_j)}{(\sum_{j=1}^{np} \overline{\xi_j})^2}.$$

Thus, the optimal q density of $\phi_{i,j}$ takes the following form:

$$q(\phi_j) \sim giG(a-1, \sum_{i=1}^{np} \overline{\xi_j}, \frac{2\sqrt{\overline{\gamma_j^2} + (\overline{V}_{jj})^2}}{\sum_{j=1}^{np} \overline{\xi_j}})$$

$$(13)$$

4.5 $q(b_1)$

$$q(b_1) \sim G(\frac{T}{2}, \overline{s}_{n,n}), \tag{14}$$

where

$$\overline{s}_{n,n} = \frac{1}{2}(s_{n,n} + tr(X'X\overline{V_n}) + \underline{s}),$$

and

$$\overline{V_n} = V_{(n-1)\times p+1:n\times p,(n-1)\times p+1:n\times p}.$$

Hence

$$\overline{b_1} = \frac{\frac{T}{2}}{\overline{s}_{n,n}}$$

$q(b_2)$ 4.6

Let $\bar{s}_{-n,n} = s_{-n,n} + \tilde{s}_{-n,n}$, where $\tilde{s}_{-n,n}$ is a $(n-1) \times 1$ vector with the j^{th} element being $tr(X'XA_j)$ and $A_j = V_{(j-1)\times p+1:j\times p,(j-1)\times p+1:j\times p}$.

$$q(b_2) \sim N(-\overline{C}\overline{s}_{-n,n},\overline{C}),$$
 (15)

where

$$\overline{C} = (2\overline{s}_{n,n}\Omega_{-n,-n}^{-1} + \overline{H}^{*-1})^{-1},$$

and

$$\overline{b_2} = (-\overline{C}\overline{s}_{-n,n}).$$

Note that $\overline{H}^* = diag(\overline{h}_{-n,n})$, and j^{th} element of $\overline{h}_{-n,n}$ is $\overline{\psi_{\omega,jn}}\overline{\phi_{\omega,jn}^2}\overline{\tau_{\omega}^2}$.

4.7 $q(\tau_{\omega})$

$$q(\tau_{\omega}) \sim giG[\frac{n^2 - n}{2}(a_{\omega} - 1), 1, \sum_{j < k} 2(\overline{\omega_{jk}}^2 + \overline{C}_{jj})^{1/2} \frac{1}{\overline{\phi_{\omega, jk}}}],^3$$
 (16)

To calculate $\overline{s}_{-i,i}$, for $i \neq n$, we need to delete the relevant $(i-1) \times p+1$ to $i \times p$ rows and $(i-1) \times p+1$ to $i \times p$ columns of \overline{V} to construct A_j .

Note that \overline{C}_{jj} changes when k changes.

Let
$$\chi_{\omega} = \sum_{j < k} 2(\overline{\omega_{jk}}^2 + \overline{V}_{jj})^{1/2}(\overline{\phi_{\omega,jk}})^{-1}$$
. We have

$$\overline{\tau_{\omega}} = \frac{\sqrt{\chi_{\omega}} K_{\frac{n^2-n}{2}(a_{\omega}-1)+1}(\sqrt{\chi_{\omega}})}{K_{\frac{n^2-n}{2}(a_{\omega}-1)}(\sqrt{\chi_{\omega}})},$$

and

$$\overline{\tau_{\omega}^{2}} = \overline{\tau_{\omega}^{2}} + \chi_{\omega} \left[\frac{K_{\frac{n^{2}-n}{2}(a_{\omega}-1)+2}(\sqrt{\chi})}{K_{\frac{n^{2}-n}{2}(a_{\omega}-1)}(\sqrt{\chi_{\omega}})} - \left(\frac{K_{\frac{n^{2}-n}{2}(a_{\omega}-1)+1}(\sqrt{\chi_{\omega}})}{K_{\frac{n^{2}-n}{2}(a_{\omega}-1)}(\sqrt{\chi_{\omega}})} \right)^{2} \right].$$

4.8 $q(\psi_{\omega,jn})$

$$q(\psi_{\omega,jn}^{-1}) \sim iG(\sqrt{\frac{\overline{\phi_{\omega,jn}^2} \, \overline{\tau_{\omega}^2}}{\overline{\omega_{jn}^2} + \overline{C}_{jj}}}, 1)$$

$$(17)$$

Let
$$\rho_{\omega} = \sqrt{\frac{\overline{\phi_{\omega,jn}^2} \, \overline{\tau_{\omega}^2}}{\overline{\omega_{jn}}^2 + \overline{C}_{jj}}}$$
.

$$\overline{\psi_{\omega,jn}^{-1}} = \rho_{\omega},$$

and

$$\overline{\psi_{w,jn}} = 1 + 1/\rho_{\omega}.$$

4.9 $q(\phi_{\omega,in})$

$$q(\xi_{\omega,jn}) \sim giG(a_{\omega} - 1, 1, 2\sqrt{\overline{\omega_{jn}}^2 + \overline{C}_{jj}})$$
 (18)

Let $\varpi_{\omega} = 2\sqrt{\overline{\omega_{jn}}^2 + \overline{C}_{jj}}$. We have

$$\overline{\xi_{\omega,jn}} = \frac{\sqrt{\overline{\omega_{\omega}}} K_{a_{\omega}}(\sqrt{\overline{\omega_{\omega}}})}{K_{a_{\omega}-1}(\sqrt{\overline{\omega_{\omega}}})},$$

and

$$var(\xi_{\omega,jn}) = \varpi_{\omega} \left\{ \frac{K_{a_{\omega}+1}(\sqrt{\varpi_{\omega}})}{K_{a_{\omega}-1}(\sqrt{\varpi_{\omega}})} - \left[\frac{K_{a_{\omega}}(\sqrt{\varpi_{\omega}})}{K_{a_{\omega}-1}(\sqrt{\varpi_{\omega}})} \right]^{2} \right\},$$

where $var(\bullet)$ denotes the variance.

Scaling $\xi_{\omega,jn}$, we have

$$\overline{\phi_{\omega,jn}} = \frac{\overline{\xi_{\omega,jn}}}{\sum_{j < k} \overline{\xi_{\omega,jk}}},$$

and

$$\overline{\phi_{\omega,jn}^2} = \overline{\phi_{\omega,jn}}^2 + \frac{var(\xi_{\omega,jn})}{(\sum\limits_{j < k} \overline{\xi_{\omega,jk}})^2}.$$

Thus, the optimal q density of $\phi_{\omega,ij}$ takes the following form:

$$q(\phi_{\omega,jn}) \sim giG(a-1, \sum_{j < k} \overline{\xi_{\omega,jk}}, \frac{2\sqrt{\overline{\omega_{jn}}^2 + (\overline{C}_{jj})^2}}{\sum_{j < k} \overline{\xi_{\omega,jk}}})$$
(19)

5 ELBO

The evidence lower bound (ELBO) is as follows:⁴

$$ELBO = E\{\log p(Y, \gamma, \tau, \psi, \phi, b_1, b_2, \tau_{\omega}, \psi_{\omega}, \phi_{\omega})\} - E\{\log q(\gamma, \tau, \psi, \phi, b_1, b_2\tau_{\omega}, \psi_{\omega}, \phi_{\omega})\}$$

$$= E\{\log p(Y|\gamma, \tau, \psi, \phi, b_1, b_2\tau_{\omega}, \psi_{\omega}, \phi_{\omega})\} + E\{\log p(\gamma)\} + \sum E\{\log p(b_1)\} + \sum E\{\log p(b_2)\}$$

$$+ E\{\log p(\phi)\} + E\{\log p(\psi)\} + E\{\log p(\tau)\} + E\{\log p(\phi_{\omega})\} + E\{\log p(\psi_{\omega})\} + E\{\log p(\tau_{\omega})\}$$

$$- E\{\log q(\gamma)\} - \sum E\{\log q(b_1)\} - \sum E\{\log q(b_2)\} - E\{\log q(\phi)\} - E\{\log q(\psi)\} - E\{\log q(\tau)\}$$

$$- E\{\log q(\phi_{\omega})\} - E\{\log q(\psi_{\omega})\} - E\{\log q(\tau_{\omega})\},$$
(20)

where

$$E\{\log p(Y|\gamma, \tau, \psi, \phi, b_1, b_2, \tau_{\omega}, \psi_{\omega}, \phi_{\omega})\} = -\frac{T}{2}log|\overline{\Sigma}| - \frac{1}{2}\left[vec(\overline{\Omega})\right]' vec(Y'Y - 2XBY' + XBB'X' + \sum_{j=1}^{n} XK_jX') + Const.,$$
(21)

with the elements of K_j retrieved from appropriate rows and columns of \overline{V} .

$$E\{\log p(\gamma)\} = -\frac{1}{2}E[\log(|V|)] - \frac{1}{2}\left[\overline{\gamma}'V^{-1}\overline{\gamma} + tr(V^{-1}\overline{V})\right] + Const., \tag{22}$$

where $E[log(|V|)] = \sum_{j=1}^{np} E[log(\psi_j) + 2 \log(\phi_j)] + 2npE[log(\tau)], E[log(\psi_j) + 2 \log(\phi_j)] = \int_0^\infty q(\psi_j) \log(\psi_j) d\psi_j + 2 \int_0^\infty q(\phi_j) \log(\phi_j) d\phi_j$ and $E[log(\tau)] = \int_0^\infty q(\tau) \log(\tau) d\tau$.

 $^{^4}$ It is seen that the ELBO described below contains many constant terms. Those terms need to be dropped from ELBOs in VB iterations to speed up the algorithm.

$$E\{\log p(b_1)\} = -(\underline{\nu} - 1)\log(\overline{s}_{n,n}) - \underline{s}\overline{b_1} + Const., \tag{23}$$

$$E\{\log p(b_2)\} = -\frac{1}{2}E(\log(|H^*|)) - \frac{1}{2}\left[\overline{b_2}'H^*\overline{b_2} + tr('H^{*-1}\overline{C})\right] + Const.,$$
 (24)

where $E[log(|H^*|)] = \sum_{j=1}^{n-1} E[log(\psi_{\omega,ij}) + 2 log(\phi_{\omega,ij})] + 2(n-1)E[log(\tau_{\omega})], E[log(\psi_{\omega,ij}) + 2 log(\phi_{\omega,ij})] = \int_0^\infty q(\psi_{\omega,ij}) log(\psi_{\omega,ij}) d\psi_{\omega,ij} + 2 \int_0^\infty q(\phi_{\omega,ij}) log(\phi_{\omega,ij}) d\phi_{\omega,ij} \text{ and } E[log(\tau_{\omega})] = \int_0^\infty q(\tau_{\omega}) log(\tau_{\omega}) d\tau_{\omega}.$

$$E\{\log p(\tau)\} = -npa \left[\int_0^\infty (q(\tau)\log \tau) d\tau \right] - 0.5\overline{\tau} + Const., \tag{25}$$

$$E\{\log p(\psi)\} = -0.5 \sum_{j=1}^{np} \overline{\psi_j} + Const., \tag{26}$$

$$E\{\log p(\phi)\} = -(a-1)\sum_{j=1}^{np} \left[\int_0^\infty (q(\phi_j)\log\phi_j)d\phi_j \right],\tag{27}$$

$$E\{\log p(\tau_{\omega})\} = -\frac{n^2 - n}{2} a_{\omega} \left[\int_0^{\infty} (q(\tau_{\omega}) \log \tau_{\omega}) d\tau_{\omega} \right] - 0.5 \left[\int_0^{\infty} (q(\tau_{\omega}) \tau_{\omega}) d\tau_{\omega} \right] + Const.,$$
(28)

$$E\{\log p(\psi_{\omega})\} = -0.5 \sum_{j=1}^{(n^2 - n)/2} \int_0^\infty (\psi_{\omega,j} q(\psi_{\omega,j})) d\psi_{\omega,j} + Const.,$$
 (29)

$$E\{\log p(\phi_{\omega})\} = -(a_{\omega} - 1) \sum_{j=1}^{(n^2 - n)/2} \left[\int_0^{\infty} (q(\phi_{\omega,j}) \log \phi_{\omega,j}) d\phi_{\omega,j} \right],$$
(30)

$$E\{\log q(\gamma)\} = -\frac{1}{2}log(|\overline{V}|) + Const., \tag{31}$$

$$E\{\log p(b_1)\} = \log(\overline{s}_{n,n}) + Const., \tag{32}$$

$$E\{\log p(b_2)\} = -\frac{1}{2}E(\log(\overline{C})) + Const., \tag{33}$$

$$E\{\log q(\tau)\} = \int_0^\infty q(\tau)\log q(\tau)d\tau,\tag{34}$$

$$E\{\log q(\psi)\} = \sum_{j=1}^{np} \int_0^\infty q(\psi_j) \log q(\psi_j) d\psi_j, \tag{35}$$

$$E\{\log q(\phi)\} = \sum_{j=1}^{np} \int_0^\infty q(\phi_j) \log q(\phi_j) d\phi_j, \tag{36}$$

$$E\{\log q(\tau_{\omega})\} = \int_{0}^{\infty} q(\tau_{\omega}) \log q(\tau_{\omega}) d\tau_{\omega}, \tag{37}$$

$$E\{\log q(\psi_{\omega})\} = \sum_{j=1}^{(n^2-2)/2} \int_0^\infty q(\psi_{\omega,j}) \log q(\psi_{\omega,j}) d\psi_{\omega,j},$$
 (38)

and

$$E\{\log q(\phi_{\omega})\} = \sum_{j=1}^{(n^2-2)/2} \int_0^\infty q(\phi_{\omega,j}) \log q(\phi_{\omega,j}) d\phi_{\omega,j}.$$
 (39)

Terms in ELBO that do not have clear analytical forms need to be numerically estimated.