A.2 Appendix

1. Structural vector autoregression model

The structural form of the vector autoregression model is given by

$$\mathbf{A_0} X_t = \sum_{i=1}^{p} \mathbf{A_i} X_{t-i} + \mathbf{B_0} Z_t + \epsilon_t, \tag{1}$$

where X_t is a $Nx1$ vector of endogenous variables, Z_t is a $Mx1$ vector of exogenous variables including the constant term, and $\epsilon_t \sim WN(0, I)$ is a $Nx1$ vector of structural shocks. In our benchmark specification we have $N = 5$, $M = 3$, $p = 1$, and $T = 59$.

The coefficient matrices are as follows. $\mathbf{A_0}$ is the NXN matrix used to identify contemporaneous relations among variables, $\mathbf{A_i}$ are the NXN coefficient matrices of lagged variables, and $\mathbf{B_0}$ is the NxM matrix of coefficients on the exogenous variables and the constant term.

We set $p = 1$ and multiply both sides of (1) by $\mathbf{A_0^-1}$ to obtain the reduced form VAR

$$X_t = \mathbf{C} X_{t-1} + \mathbf{D} Z_t + \mathbf{u_t} \tag{2}$$

where $\mathbf{C} = \mathbf{A_0^{-1} A_1}$, $\mathbf{D} = \mathbf{A_0^{-1} B_0}$, and $\mathbf{u_t} \sim \mathbf{N(0, \Sigma)}$.

A compact representation of (2) can be obtained

$$\mathbf{Y} = \mathbf{EW} + \mathbf{U},$$

where

$$\mathbf{Y}_{NxT} = (X_1, \cdots, X_T)$$

$$\mathbf{E}_{Nx(N+M)} = (\mathbf{C}, \mathbf{D})$$

$$\mathbf{W}_{(N+M)xT} = \begin{pmatrix} \mathbf{Y_0}, \cdots, \mathbf{Y_{T-1}} \\ \mathbf{Z_1}, \cdots, \mathbf{Z_T} \end{pmatrix}$$

$$\mathbf{U}_{NxT} = (\mathbf{u_1}, \cdots, \mathbf{u_T}),$$

and

$$\mathbf{u}_t = \mathbf{A_0^{-1}} \epsilon_t.$$

Estimation entails obtaining a matrix of estimated coefficients $\hat{\mathbf{E}}$, and the ensuing matrix of residuals from $\hat{\mathbf{U}} = \mathbf{Y} - \hat{\mathbf{E}}\mathbf{W}$.

For easier manipulation, and without loss of generality, let us consider the SVAR model in (1) without the exogenous block

$$X_t = \mathbf{C} X_{t-1} + \mathbf{u_t}, \tag{3}$$

which can be written as

$$(\mathbf{I} - \mathbf{C(L)}) X_t = \mathbf{u_t}, \tag{4}$$

In compact form

$$X_t = \mathbf{F(L)} \mathbf{A_0^{-1}} \epsilon_t, \tag{5}$$

where $\mathbf{F(L)} = (\mathbf{I} - \mathbf{C(L)})^{-1}$ can be obtained from estimating $\mathbf{C}$ and inverting $\mathbf{A_0}$ from (2). We use short-run recursive identification, which entails setting restrictions on $\mathbf{A_0}$.

The identification strategy is implemented as follows. Multiply both sides of (4) by a matrix of parameters $\mathbf{A_{NxN}}$ and equate the resulting expression to a scaled version of the i.i.d vector ϵ_t using a scaling matrix $\mathbf{B_{NxN}}$.

$$\mathbf{A}(\mathbf{I} - \mathbf{C(L)}) X_t = \mathbf{A u_t} = \mathbf{B} \epsilon_t$$

,

The identification strategy is discussed in the paper and is implemented by setting $\mathbf{A}$ as a lower triangular matrix with ones on the diagonal, and $\mathbf{B}$ as a diagonal matrix.

Implementation is achieved by using the Cholesky decomposition of $\mathbf{\Sigma}$, the covariance matrix of $\mathbf{u_t}$, such that $\mathbf{\Sigma} = \mathbf{SS'}$. In this case $\mathbf{S} = \mathbf{A^{-1}B} = \mathbf{A_0^{-1}}$.

2. Parameter estimates

Here we report the coefficients from estimating the benchmark specification from **Figure 1** in the paper.

$$A = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 0.04 & 1 & 0 & 0 & 0 \\ -0.05 & -0.02 & 1 & 0 & 0 \\ -0.12 & -0.16 & 0.72 & 1 & 0 \\ 0.01 & -0.13 & -0.03 & 0.05 & 1 \end{pmatrix}$$

$$B = \begin{pmatrix} 0.79 & 0 & 0 & 0 & 0 \\ 0 & 0.71 & 0 & 0 & 0 \\ 0 & 0 & 0.26 & 0 & 0 \\ 0 & 0 & 0 & 0.48 & 0 \\ 0 & 0 & 0 & 0 & 0.36 \end{pmatrix},$$

and the resulting Cholesky factor $\mathbf{S} = \mathbf{A^{-1}B}$ is

$$A = \begin{pmatrix} 0.79 & 0 & 0 & 0 & 0 \\ -0.03 & 0.71 & 0 & 0 & 0 \\ 0.04 & 0.01 & 0.26 & 0 & 0 \\ 0.06 & 0.10 & -0.18 & 0.48 & 0 \\ -0.01 & 0.09 & 0.02 & -0.02 & 0.36 \end{pmatrix}.$$