Solving Linear Rational Expectations Models

Form of System

We'll start with

$$AE_tY_{t+1} = BY_t$$

· We'll end with

$$Y_{t+1} = GY_t + H\varepsilon_{t+1}$$

Necessary condition for solvability

- There must be a "z" (scalar number) such that |Az-B| is not zero.
- Weaker than |A| not zero (required for inverse); can have |A|=0 or |B|=0 or both.
- If there is such a z, then one can construct full rank matrices for transforming system
 - T transforms equations
 - V transforms variables.

Transformed System

General form

$$A^* E_t Y_{t+1}^* = B^* Y_t^*$$

with
$$A^* = TAV^{-1}; B^* = TBV^{-1}$$

Form of Transformed System

- Key matrices are block diagonal
- Jordan matrices with stable and unstable eigenvalues as in Blanchard-Kahn (1980)
- "N" is nilpotent (zeros on diagonal and below; ones and zeros above diagonal).

$$A^* = \begin{bmatrix} N & 0 & 0 \\ 0 & I & 0 \\ 0 & 0 & I \end{bmatrix} \text{ and } B^* = \begin{bmatrix} I & 0 & 0 \\ 0 & J_u & 0 \\ 0 & 0 & J_s \end{bmatrix}$$

An aside

- Solutions to |Az-B|=0 are called "generalized eigenvalues of A,B"
- Since roots of the polynomial are not affected by multiplication by arbitrary nonsingular matrices, these are the same as "generalized eigenvalues of A*,B*" i.e., the roots of |A*z-B*|=0.
- With a little work, you can see that there are only as many roots as n(μ_u)+n(μ_s), since there are zeros on the diagonal of N. Try the case at right for intuition

$$A^* = egin{bmatrix} 0 & 0 & 0 \ 0 & 1 & 0 \ 0 & 0 & 1 \end{bmatrix}$$
 $B^* = egin{bmatrix} 1 & 0 & 0 \ 0 & \mu_u & 0 \ 0 & 0 & \mu_s \end{bmatrix}$

Implications

 Transformed variables which evolve according to separated equation systems

Three types of "canonical variables"

Unstable canonical variables

$$E_t u_{t+1} = J_u u_t \Rightarrow u_t = 0$$

so as to avoid explosive behavior

Stable canonical variables

$$E_t s_{t+1} = J_s s_t$$

Infinite eigenvalue canonical variables

$$NE_t i_{t+1} = i_t \Rightarrow i_t = 0$$

Just like unstable

Solving for the variables we really care about

 Partition Y into those variables that are predetermined or have exogenous forecast error (K) and every thing else (Λ)

$$Y_t = \left[egin{array}{c} \Lambda_t \ K_t \end{array}
ight]$$

Group i and u variables into U

$$U_t = \begin{bmatrix} i_t \\ u_t \end{bmatrix}$$

Partition the variable transformation

$$\begin{bmatrix} U \\ U \end{bmatrix} = \begin{bmatrix} V_{U\Lambda} & V_{UK} \\ V_{S\Lambda} & V_{SK} \end{bmatrix} \begin{bmatrix} \Lambda \\ K \end{bmatrix}$$

$$egin{bmatrix} \Lambda \ K \end{bmatrix} = egin{bmatrix} R_{\Lambda U} & R_{\Lambda s} \ R_{KU} & R_{Ks} \end{bmatrix} egin{bmatrix} U \ S \end{bmatrix}$$

 Solve for nonpredetermined or exogenous variables given solutions for U = 0.

$$\Lambda_t = -V_{U\Lambda}^{-1} V_{UK} K_t$$

Need square and nonsingular matrix

Condition #1: counting rule

- Need same number of elements of Λ as unstable and infinite eigenvalues number (number of elements of U).
- But this implies: number of stable eigenvalues = (number of elements of S) number of variables with predetermined or exogenous forecast error (number of elements of K).
- This condition is due to Blanchard and Kahn (1980) in terms of predetermined variables and was generalized to variables that have exogenous forecast errors by Sims and Klein

Condition #2: rank condition

- But it is not enough for the matrix $V_{U\Lambda}$ to be square: it must be nonsingular to be inverted.
- This condition was present in Blanchard-Kahn (1980) and was emphasized in the generalization of King and Watson (1998).
- A parallel condition is in Sims, Klein and the result is reported in Dynare.

Solving for other variables

 Use the reverse transform, the solution for the stable variables, and the solution for the U variables (unstable and infinite cvs)

$$\begin{split} E_{t}K_{t+1} &= R_{KU}E_{t}U_{t+1} + R_{Ks}E_{t}s_{t+1} \\ &= 0 + R_{Ks}J_{s}s_{t} \\ &= R_{Ks}[J_{s}(V_{s\Lambda}\Lambda_{t} + V_{sK}K_{t})] \\ &= R_{Ks}J_{s}(V_{s\Lambda}V_{U\Lambda}^{-1}V_{UK} + V_{sK})K_{t} \end{split}$$

Now we know

$$\begin{split} \Lambda_{t+1} &= V_{U\Lambda}^{-1} V_{UK} \ K_{t+1} \\ E_t K_{t+1} &= R_{Ks} J_s (V_{s\Lambda} V_{U\Lambda}^{-1} V_{UK} + V_{sK}) \ K_t \\ &= G_K Y_t \\ K_{t+1} &= E_t K_{t+1} + H_K \varepsilon_{t+1} \\ &= G_K Y_t + H_K \varepsilon_{t+1} \\ \Lambda_{t+1} &= V_{U\Lambda}^{-1} V_{U\underline{K}} \ E_t K_{t+1} + V_{U\Lambda}^{-1} V_{U\underline{K}} H_K \varepsilon_{t+1} \\ &= G_{\Lambda} Y_t + H_{\xi} \varepsilon_{t+1} \\ \end{split}$$

Done!

- System is now in the form reported in main page
- However, this is a theoretical characterization, not a numerical recipe
- Numerical recipes employ the "Generalized Schur decomposition" which makes matrices like N and J upper triangular. This is a numerically more stable approach, but all the logical components are the same.