



Optimal policy in Rational Expectations Model: New Solution Algorithms

Dennis (2005 *forthcoming*) Macro Dynamics

Philip Liu

Division of Economics

Research School of Pacific and Asian Studies

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Motivation

- ✓ Previous solution algorithms Oudiz and Sachs (1985), Currie and Levine (1985,1993), Backus and Driffill (1986), and Soderlind (1999) require constraints to be written in state-space form
- ✓ Allow constraints in structural form, no need to distinguish between predetermine and jump variables
- ✓ Include next period's policy instrument(s) in the optimization constraint
- ✓ Easier to apply in practice especially when one is considering many different medium-scale models



Overview of the paper

- ✓ Small contribution but significant in terms of practicality
- ✓ “New” algorithm to solve optimal policy in rational expectation models
- ✓ Central bank’s control problem, under both commitment and discretion
- ✓ Easily understood
- ✓ Applied to three different models, test for efficiency
- ✓ Provide some insights into the convergence problems

Compare to S.S specification

✓ Soderlind (1999) and co

$$Loss(t, \infty) = E_t \sum_{t=0}^{\infty} \beta^t [y_t' W y_t + x_t' Q x_t], \quad (1)$$

$$\text{s.t: } y_{t+1} = A y_t + B x_t + C \varepsilon_{t+1}, \quad (2)$$

$$\text{where } y_{t+1} = \begin{bmatrix} y_{1t+1} & E_t y_{2t+1} \end{bmatrix}'.$$

✓ Dennis (2005)

$$Loss(t, \infty) = E_t \sum_{t=0}^{\infty} \beta^t [y_t' W y_t + x_t' Q x_t], \quad (3)$$

$$\text{s.t: } A_0 y_t = A_1 y_{t-1} + A_2 E_t y_{t+1} + A_3 x_t + A_4 E_t x_{t+1} + A_5 v_t. \quad (4)$$

Commitment - The Problem

CB choose the path of y_t , x_t and λ_t , $\forall t \geq 0$, and commit to it:

$$L = E_t \sum_{t=0}^{\infty} \beta^t [y_t' W y_t + x_t' Q x_t + 2\lambda_t' (A_0 y_t - A_1 y_{t-1} - A_2 y_{t+1} - A_3 x_t - A_4 x_{t+1} - \rho_t)] \quad (5)$$

$$\frac{dL}{dx_t} = Q x_t - A_3' \lambda_t - \beta^{-1} A_4' \lambda_{t-1} = 0, \quad t > 0; \quad (6a)$$

$$\frac{dL}{dy_t} = W y_t + A_0' \lambda_t - \beta^{-1} A_2' \lambda_{t-1} - \beta A_1' E_t \lambda_{t+1} = 0, \quad t > 0; \quad (6b)$$

$$\frac{dL}{d\lambda_t} = A_0 y_t - A_1 y_{t-1} - A_2 E_t y_{t+1} - A_3 x_t - A_4 E_t x_{t+1} - A_5 v_t = 0, \quad t \geq 0; \quad (6c)$$

$$\frac{dL}{dx_t} = Q x_t - A_3' \lambda_t = 0, \quad t = 0; \quad (6d)$$

$$\frac{dL}{dy_t} = W y_t + A_0' \lambda_t - \beta A_1' E_t \lambda_{t+1} = 0, \quad t = 0. \quad (6e)$$

Only (6a) to (6c) will be binding, or $\lambda_0 = 0$

Commitment - The solution

Write equations (6a-6c) as $AZ_t = BZ_{t-1} + CE_tZ_{t+1} + Dv_t$:

$$\underbrace{\begin{bmatrix} 0 & A_0 & -A_3 \\ A'_0 & W & 0 \\ -A'_3 & 0 & Q \end{bmatrix}}_{(2n+p) \times (2n+p)} \begin{bmatrix} \lambda_t \\ y_t \\ \mathbf{x}_t \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & A_1 & 0 \\ \beta_{-1}A'_2 & 0 & 0 \\ \beta_{-1}A'_4 & 0 & 0 \end{bmatrix}}_{(2n+p) \times (2n+p)} \begin{bmatrix} \lambda_{t-1} \\ y_{t-1} \\ \mathbf{x}_{t-1} \end{bmatrix} \quad (7)$$

$$+ \underbrace{\begin{bmatrix} 0 & A_2 & A_4 \\ \beta A'_1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}}_{(2n+p) \times (2n+p)} E_t \begin{bmatrix} \lambda_{t+1} \\ y_{t+1} \\ \mathbf{x}_{t+1} \end{bmatrix} + \underbrace{\begin{bmatrix} A_5 \\ 0 \\ 0 \end{bmatrix}}_{(2n+p) \times s} [v_t]$$

Binder and Pesaran (1995) **Solution:** $Z_t = HZ_{t-1} + Gv_t \quad (8)$

Commitment - Remarks

1. Can also solve equations (6a-6c) using eigenvalue methods
2. The Euler equations (6a-6c) do not depend on Ω - **certainty equivalent**. Special property under quadratic objective, linear constraints and v_t is a Martingale sequence

3. $Loss(t, \infty) = \left[Z_t' \hat{P} Z_t + \frac{\beta}{1-\beta} tr(G' \hat{P} G \Omega) \right]$, where

$$\hat{P} \equiv \hat{K} + \beta H' \hat{P} H, \text{ and } \hat{K} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & W & 0 \\ 0 & 0 & Q \end{bmatrix}$$

4. $\lim_{\beta \uparrow 1} (1 - \beta) Loss(t, \infty) = tr(K \Phi)$, where Φ is the

unconditional var-cov of $[y_t' \ x_t']'$ and $K = \begin{bmatrix} W & 0 \\ 0 & Q \end{bmatrix}$

Discretion - The Problem

$$Loss(t, \infty) = E_t \sum_{t=0}^{\infty} \beta^t [y_t' W y_t + x_t' Q x_t], \quad (9)$$

$$\text{s.t: } A_0 y_t = A_1 y_{t-1} + A_2 E_t y_{t+1} + A_3 x_t + A_4 E_t x_{t+1} + A_5 v_t. \quad (10)$$

$$\text{Conjecture: } y_t = H_1 y_{t-1} + H_2 v_t \quad (11)$$

$$x_t = F_1 y_{t-1} + F_2 v_t \quad (12)$$

$$Loss(t, \infty) = y_t' P y_t + x_t' Q x_t + \frac{\beta}{1 - \beta} \text{tr}[(F_2' Q F_2 + H_2' P H_2) \Omega] \quad (13)$$

$$\text{s.t: } D y_t = A_1 y_{t-1} + A_3 x_t + A_5 v_t. \quad (14)$$

$$P \equiv W + \beta F_1' Q F_1 + H_1' P H_1 \quad \text{and} \quad D \equiv A_0 - A_2 H_1 - A_4 F_4$$

Discretion - The solution

$$\begin{aligned} Loss(t, \infty) &= (A_1 y_{t-1} + A_3 x_t + A_5 v_t)' D'^{-1} P D^{-1} (A_1 y_{t-1} + A_3 x_t + A_5 v_t) \\ &\quad + x_t' Q x_t + \frac{\beta}{1 - \beta} tr[(F_2' Q F_2 + H_2' P H_2) \Omega] \end{aligned}$$

$$\begin{aligned} \frac{dLoss(t, \infty)}{dx_t} &= A_2' D'^{-1} P D^{-1} (A_1 y_{t-1} + A_3 x_t + A_5 v_t) + Q x_t \\ &= A_2' D'^{-1} P D^{-1} (A_1 y_{t-1} + A_5 v_t) + (Q + A_2' D'^{-1} P D^{-1} A_3) x_t = 0 \end{aligned}$$

$$\begin{aligned} x_t &= (Q + A_2' D'^{-1} P D^{-1} A_3)^{-1} A_2' D'^{-1} P D^{-1} (A_1 y_{t-1} + A_5 v_t) \quad (15a) \\ &\equiv F_1 y_{t-1} + F_2 v_t \end{aligned}$$

$$\begin{aligned} y_t &= D^{-1} (A_1 + A_3 F_1) y_{t-1} + D^{-1} (A_5 + A_3 F_2) v_t \quad (15b) \\ &\equiv H_1 y_{t-1} + H_2 v_t \end{aligned}$$

Given H_1^0, H_2^0, F_1^0 and $F_2^0 \Rightarrow$ solve for H_1, H_2, F_1 and F_2

Solving a Riccati equation

A simple example: $G = AGB + V$.

S1: Given G_0 , start at $j = 1$;

S2: Calculate G_1 using $G_1 = AG_0B + V$;

S3: Repeat S2 using $G_{j+1} = AG_jB + V$;

S4: Stop when $|G_{j+1} - G_j| \leq \epsilon$.

```
function [g1]=ricatti(a, b, v, eps, maxiters)
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```
g0=.01*eye(length(a)); j= 1; lenj = 1;
```

```
while lenj >= eps && j<=maxiters;
```

```
    g1 = v+a*g0*b;
```

```
    lenj = max(max(abs(g1-g0)));
```

```
    g0 = g1;
```

```
    j = j + 1;
```

```
end;
```

Discretion - Remarks

1. Solving for H_1, H_2, F_1 and F_2 is generally very efficient
2. The matrices H_1, H_2, F_1 and F_2 are independent of Ω and y_0 , certainty equivalent result still holds.

3. $Loss(t, \infty) = \left[Z_t' \tilde{P} Z_t + \frac{\beta}{1-\beta} tr(G' \tilde{P} G \Omega) \right]$, where

$$Z_t = [y_t' \quad x_t']', \tilde{P} \equiv K + \beta H' \tilde{P} H, \text{ and } K = \begin{bmatrix} W & 0 \\ 0 & Q \end{bmatrix}$$

4. $\lim_{\beta \uparrow 1} (1 - \beta) Loss(t, \infty) = tr(K \Phi)$, where Φ is the unconditional var-cov of Z_t
5. Solution under discretion is generally faster than commitment because of the smaller state vector, $Z_t = [y_t' \quad x_t']'$ rather than $Z_t = [\lambda_t' \quad y_t' \quad x_t']'$

A simple application

- ✓ Apply to Gali and Monacelli (2004) to see if the new algorithm is “practical” for estimation purposes
- ✓ The model:

$$y_t = E_t y_{t+1} - \frac{1 + \alpha(2 - \alpha)(\sigma\eta - 1)}{\sigma} (i_t - E_t \pi_{t+1}) + g_t \quad (16a)$$

$$\pi_t = \beta E_t \pi_{t+1} + \frac{(1 - \theta)(1 - \theta\beta)}{\theta} \left(\phi + \frac{\sigma}{1 + \alpha(2 - \alpha)(\sigma\eta - 1)} \right) y_t + u_t \quad (16b)$$

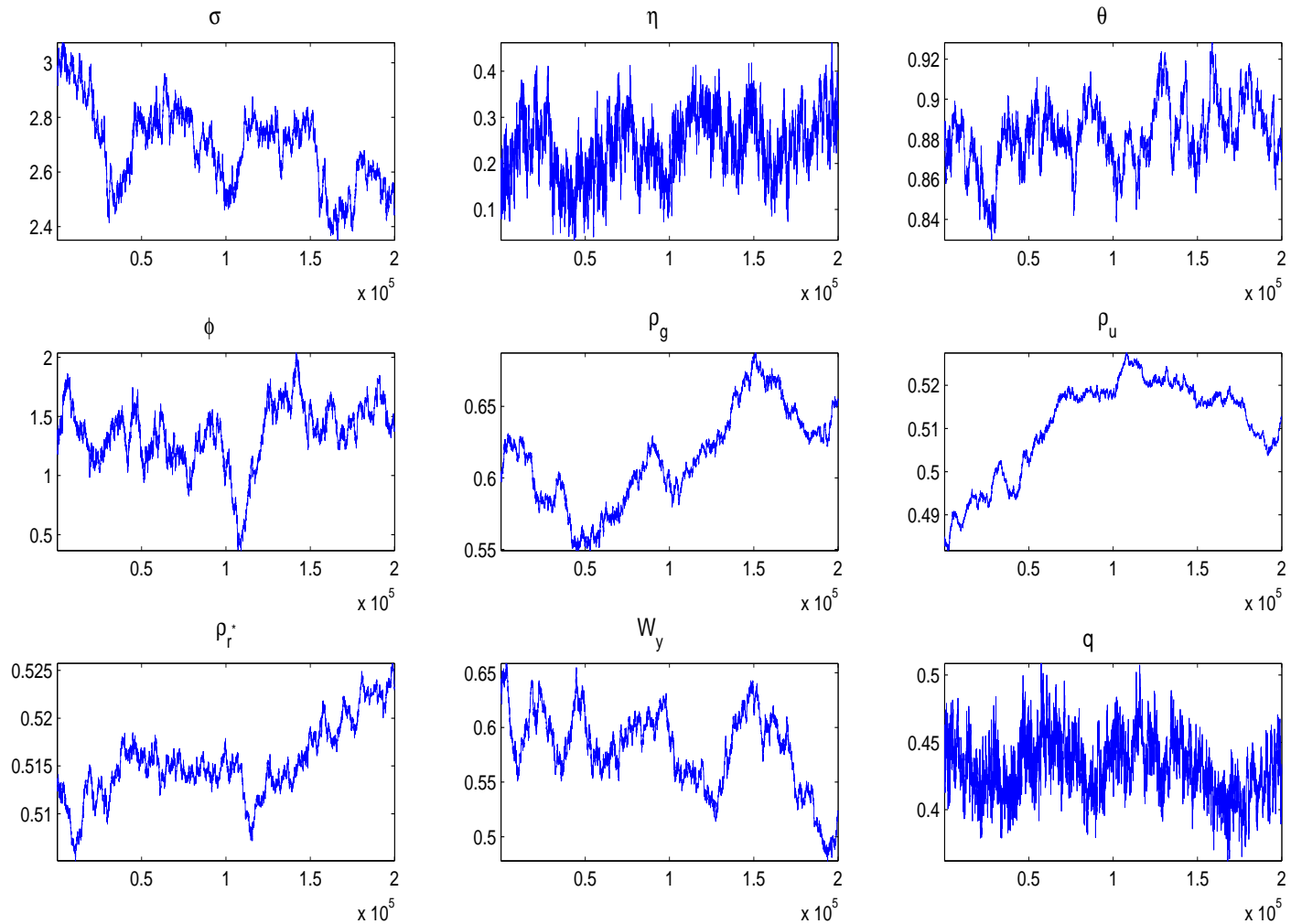
$$\pi_t^c = \pi_t + \frac{\alpha}{1 - \alpha} (q_t - q_{t-1}) \quad (16c)$$

$$q_t = E_t q_{t+1} - (1 - \alpha)(i_t - E_t \pi_{t+1} - r_t^*) + (1 - \alpha)\epsilon_t^q \quad (16d)$$

g_t, u_t and r_t^* are AR(1) processes with white noise terms $\epsilon_t^g, \epsilon_t^u, \epsilon_t^{r^*}$

- ✓ Takes around 5 hours to simulate 100k MCMC draws under discretion, and 7.5 hours under commitment on a P4 2.4G
- ✓ Haven't managed to get MLE working yet

Markov Chain - Discretion



Markov Chain - Discretion

