Materials 12 - tinkering around with policy and expectation formation

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Overview

1 Model summary

$$x_t = -\sigma i_t + \hat{\mathbb{E}}_t \sum_{T=t}^{\infty} \beta^{T-t}\big((1-\beta)x_{T+1} - \sigma(\beta i_{T+1} - \pi_{T+1}) + \sigma r_T^n\big) \tag{1}$$

$$\pi_t = \kappa x_t + \hat{\mathbb{E}}_t \sum_{T=t}^{\infty} (\alpha\beta)^{T-t}\big(\kappa\alpha\beta x_{T+1} + (1-\alpha)\beta\pi_{T+1} + u_T\big) \tag{2}$$

$$i_t = \psi_\pi \pi_t + \psi_x x_t + \rho i_{t-1} + \bar{i}_t \tag{3}$$

$$\hat{\mathbb{E}}_t z_{t+h} = \begin{bmatrix} \bar{\pi}_{t-1} \\ 0 \\ 0 \end{bmatrix} + b h_x^{h-1} s_t \quad \forall h \geq 1 \qquad b = g_x\, h_x \qquad \text{PLM} \tag{4}$$

$$\bar{\pi}_t = \bar{\pi}_{t-1} + k_t^{-1} \underbrace{\big(\pi_t - (\bar{\pi}_{t-1} + b_1 s_{t-1})\big)}_{\text{fcst error using (4)}} \qquad (b_1 \text{ is the first row of } b) \tag{5}$$

$$k_t = \begin{cases} k_{t-1} + 1 & \text{for decreasing gain learning} \\ \bar{g}^{-1} & \text{for constant gain learning.} \end{cases} \tag{6}$$

2 Changes

1. To policy
   (a) $\mathbb{E}(\pi)$ instead of π in TR
   (b) Check the fake $\psi_\pi < 1$ exercise.
2. To expectation formation
   (a) Curiosity: check IRFs from Euler equation learning
   (b) IRFs from vector learning (meaning learn all observables)
   (c) Different implications from Bayesian learning?

Some reasoning (motivation and results):

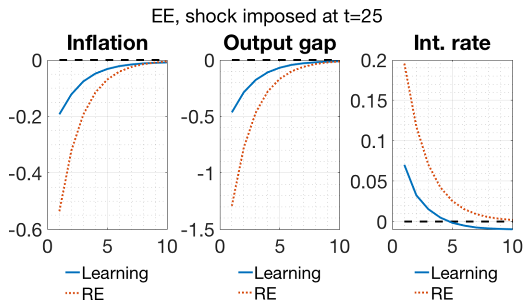
1. $\mathbb{E}(\pi)$ instead of π in TR: indeed makes overshooting larger in magnitude b/c policy is reacting to something that moves more.
2. $\psi_\pi \leq 1$: indeed kills the overshooting, but - no surprise - makes observables unstable (IRFs don't return to steady state). Why does it work to kill the overshooting? B/c the Ball-effect of anticipated interest rate reactions no longer overweighs.
3. Townsend (1983) investigates "forecasting the forecasts of others" and finds damped oscillations $\rightarrow$ do higher-order beliefs play a role for causing oscillations in learning? If so, EE learning IRFs should exhibit no oscillations (and indeed they do not!)
4. Vector learning: are model implications different when agents learn the LOM of not only inflation but also of the other variables? $\rightarrow$ No. (Note: I'm using the same gain for all variables.)
5. Does learning both slope and constant make a difference? $\rightarrow$ Yes, in particular for constant gain learning. 2 effects: 1) less foresight, so i needs to be less expansionary 2) more bumpy IRFs.

   1) I think what might be going on here is that the only thing agents now know is h_x. Therefore the Ball-type "disinflationary boom"-effect happens to a lesser extent b/c agents do not internalize movements in the interest rate in response to future inflation as much as they would otherwise.

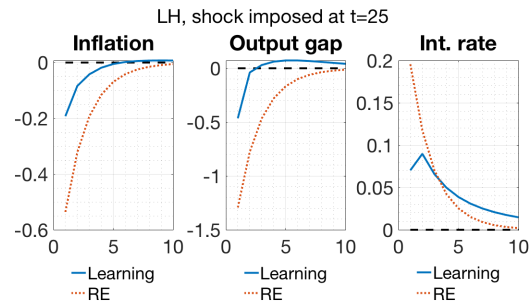
   2) More bumpy because since you're learning b, the loading on shocks, the specific sequence of shocks matters. Increasing the size of the cross-section, N, mitigates this somewhat.

3 IRFs from vector learning: EE and LH, $T = 400, N = 100$

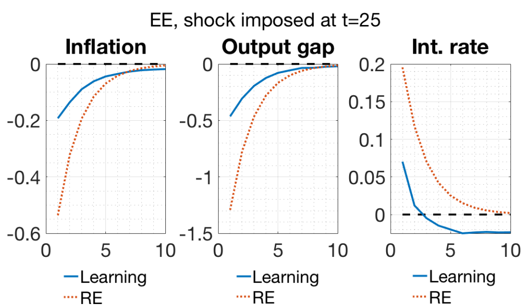
Figure 1: Learning constant only



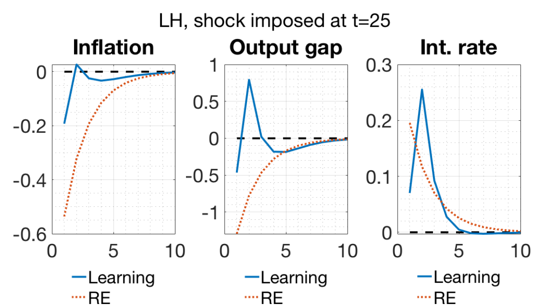
(a) EE, dgain



(b) LH, dgain

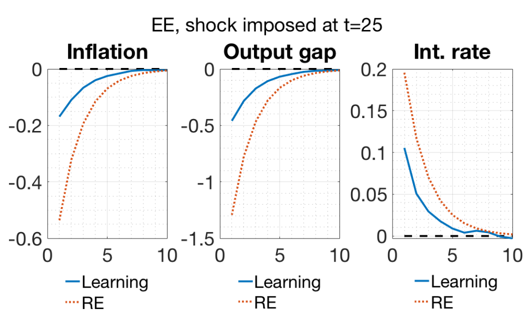


(c) EE, cgain

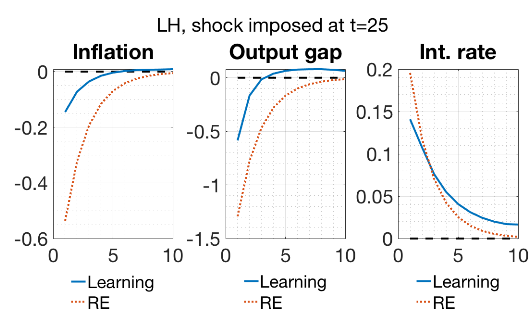


(d) LH, cgain

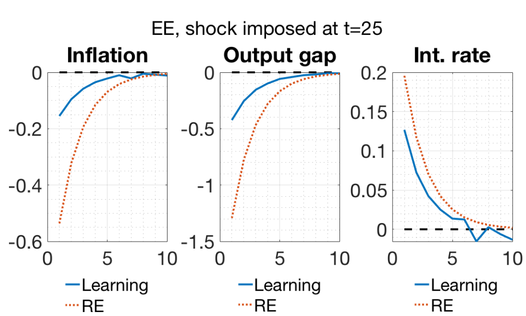
Figure 2: Learning slope and constant



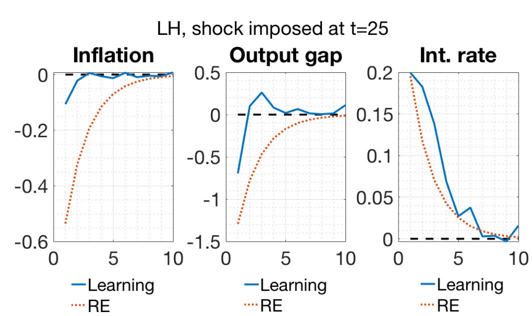
(a) EE, dgain



(b) LH, dgain



(c) EE, cgain



(d) LH, cgain

4 A technical note on the projection facility

Contrary to Liam Graham, I never have explosive path issues for long-horizon learning, but I do sometimes for Euler-equation learning (Graham claims this is never an issue for EE learning). Graham's solution for the projection facility is to check the eigenvalues of the learning matrix ϕ. My silly issue is that ϕ is not square. Therefore what I do is I check the eigenvalues of the following cheating matrix $\phi\phi'^{1/2}$. Thoughts?

5 Investigating IRFs in the data - Valerie Ramey's handbook chapter and the more bumpy local projection IRFs