Materials 14 - Maybe a last attempt to get rid of the overshooting

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January 25, 2020

Overview

1 Model summary

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

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

$$i_t = \psi_\pi \pi_t + \psi_x x_t + \bar{i}_t \tag{3}$$

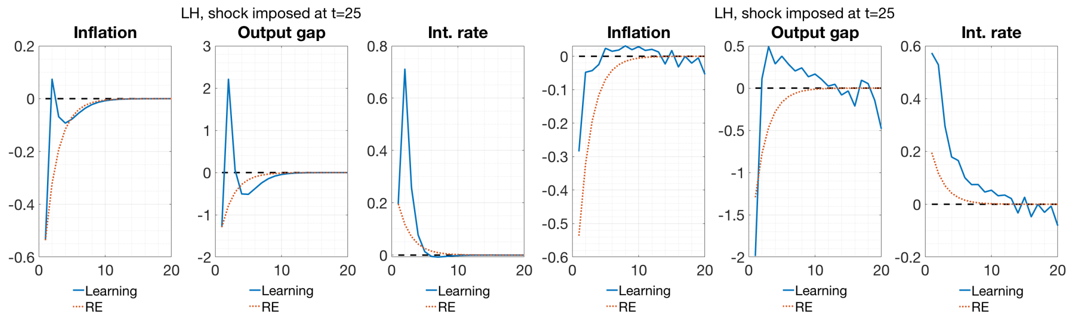
$$\hat{\mathbb{E}}_t z_{t+h} = \bar{z}_{t-1} + b h_x^{h-1} s_t \quad \forall h \geq 1 \qquad b = g_x\ h_x \qquad \text{PLM} \tag{4}$$

$$\bar{z}_t = \bar{z}_{t-1} + k_t^{-1} \underbrace{\big(z_t - (\bar{z}_{t-1} + b s_{t-1})\big)}_{\text{fcst error using (4)}} \tag{5}$$

(Vector learning. For scalar learning, $\bar{z} = \begin{pmatrix} \bar{\pi} & 0 & 0 \end{pmatrix}'$. I'm also not writing the case where the slope b is also learned.)

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

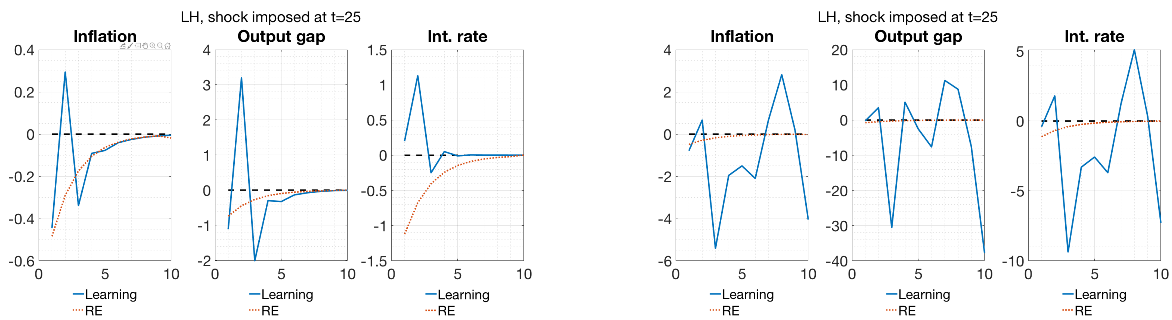
Figure 1: Reference: baseline model



(a) Learning constant only (b) Learning slope and constant

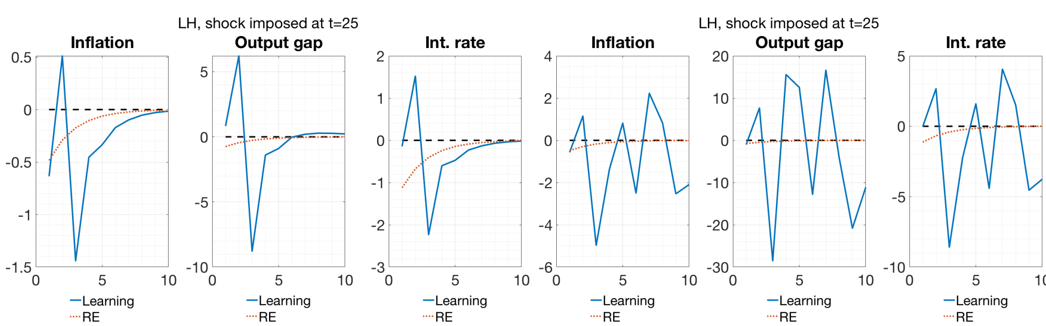
2 Regime-switching

Figure 2: Markov-switching Taylor rule, baseline, learning initialized at active state



(a) Learning constant only (b) Learning slope and constant

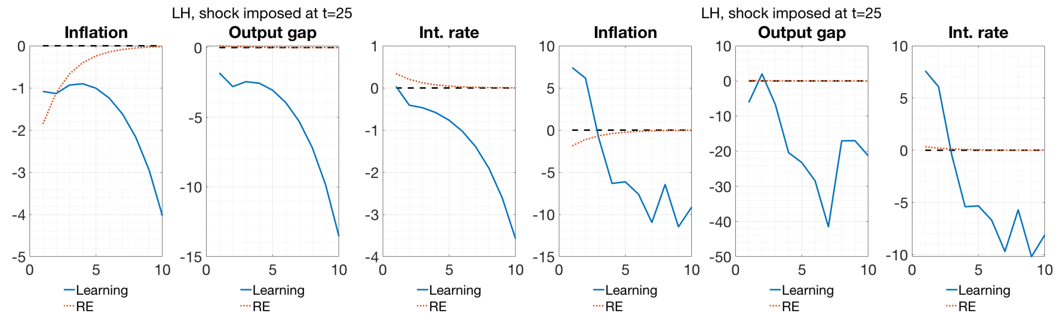
Figure 3: Markov-switching Taylor rule, baseline, learning initialized at passive state



(a) Learning constant only (b) Learning slope and constant

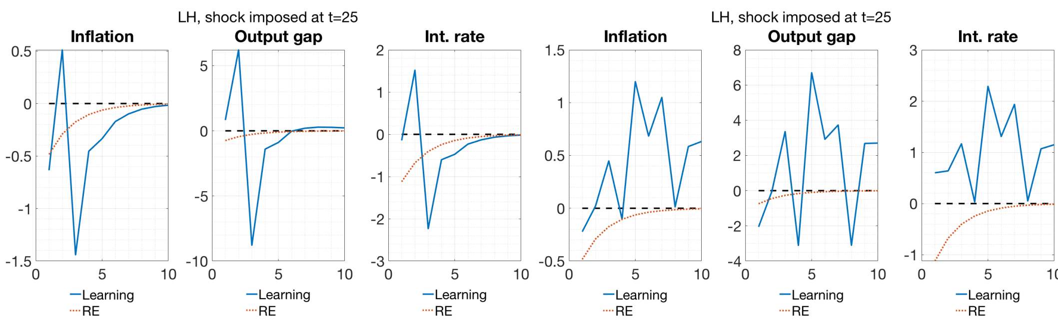
- Different initialization of learning doesn't make a whole lot of difference.
- It just changes where you start, but doesn't fundamentally affect dynamics.

Figure 4: Markov-switching Taylor rule, baseline, learning initialized at passive state, conditional on passive regime only



(a) Learning constant only (b) Learning slope and constant

Figure 5: Markov-switching Taylor rule, baseline, learning initialized at passive state, conditional on active regime only



(a) Learning constant only (b) Learning slope and constant

- I'm surprised that the all-passive state is unstable. I've checked and it's not E-stable: the difference in the learning matrix ϕ grows over time, even with decreasing gain learning.
- The all-active is very volatile.

3 Projection facility: checking `eig(phi)` when ϕ isn't square?

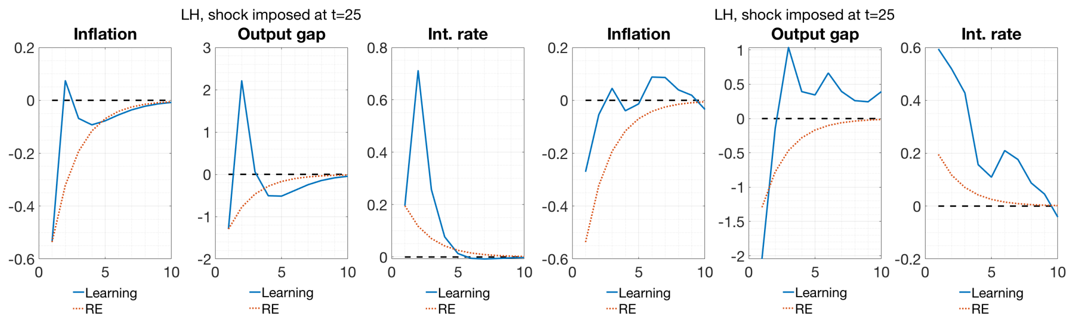
What I do now is I check `eig(R)` because that is always square, and when ϕ explodes, usually R does too. Of course I can't do this for learning the constant only, but according to my experience, that's where the projection facility is least likely to ever be needed. Of course, this doesn't always work - for interest rate smoothing, it doesn't.

4 Endogenous states don't evolve as they should

Now they do!

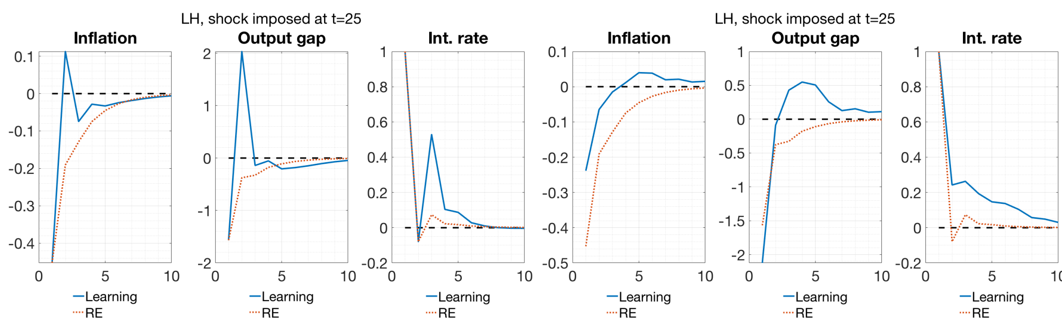
5 Reference plots

Figure 6: Baseline



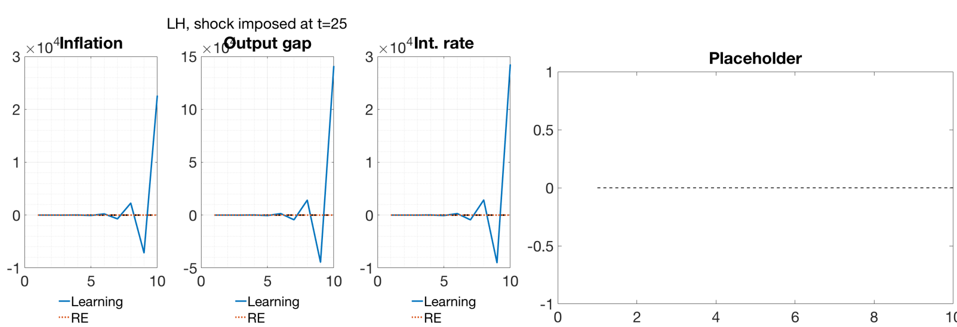
(a) Learning constant only (b) Learning slope and constant

Figure 7: Lagged inflation in Taylor rule, "suboptimal forecasters" info assumption



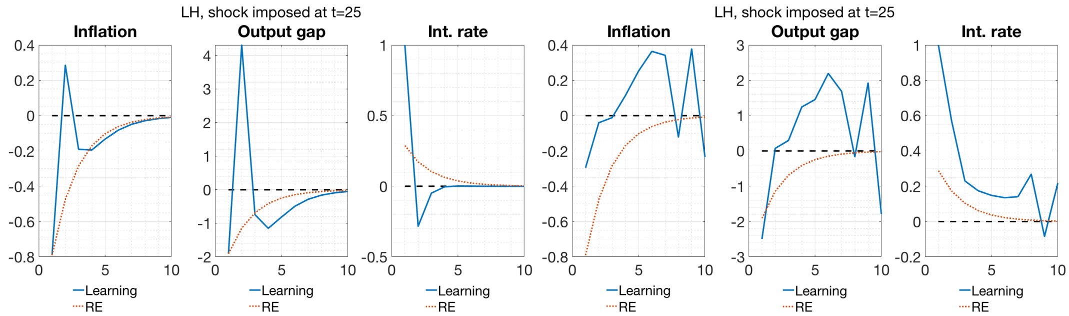
(a) Learning constant only (b) Learning slope and constant

Figure 8: Interest rate smoothing, "suboptimal forecasters" info assumption



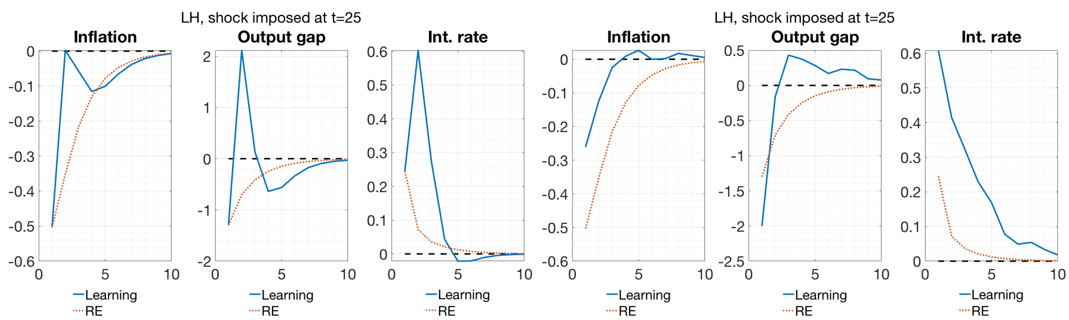
(a) Learning constant only (b) Learning slope and constant - no projection facility in the world can make this not explode

Figure 9: Expected inflation in Taylor rule



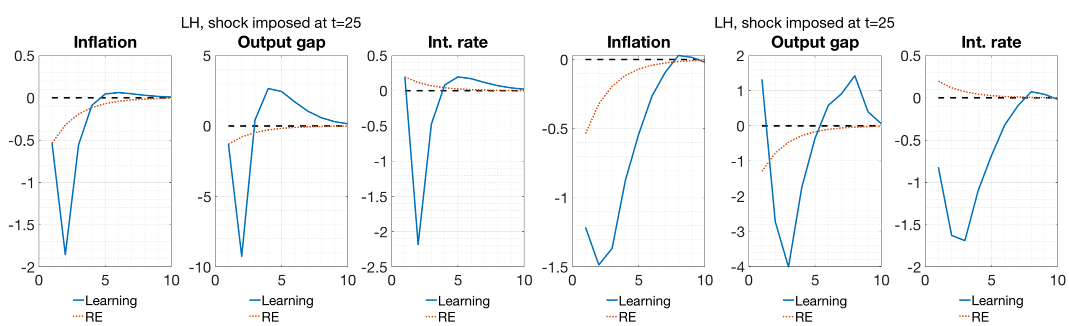
(a) Learning constant only (b) Learning slope and constant

Figure 10: Indexation in NKPC, "suboptimal forecasters" info assumption



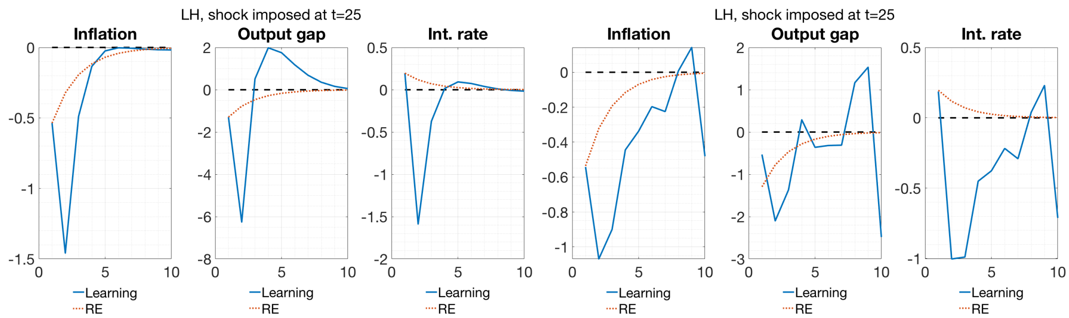
(a) Learning constant only (b) Learning slope and constant

Figure 11: Learn Taylor rule



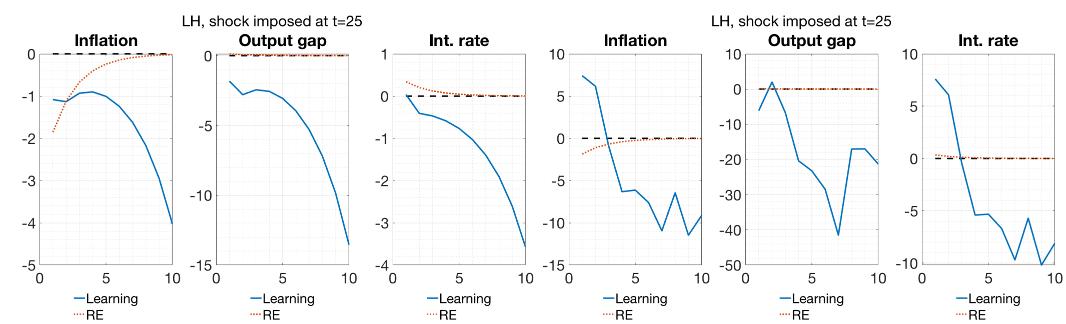
(a) Learning constant only (b) Learning slope and constant

Figure 12: Learn h_x



(a) Learning constant only (b) Learning slope and constant

Figure 13: Markov-switching Taylor rule, conditional on passive regime only, learning initialized at passive regime



(a) Learning constant only (b) Learning slope and constant