# Materials 4 - DW prep

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## 1 Timeline in the learning models

 $\underline{t=0}$ : Initialize learning coefficients  $\phi_{t-1}=\phi_0$  at the RE solution. For each t:

- 1. Evaluate expectations t + s (the one-period ahead, (s = 1) or the full 1 to  $\infty$ -period ahead  $(s = 1, ..., \infty)$ ) given  $\phi_{t-1}$  and states dated t
- 2. Evaluate ALM given expectations: "today's observables are a function of expectations and today's state"
- 3. Update learning:  $\phi_t = \text{RLS of } \phi_{t-1}$  and fcst error between today's data and yesterday's forecast

#### 2 The models

#### 2.1 Rational expectations NK model (RE)

$$x_t = \mathbb{E}_t x_{t+1} - \sigma(i_t - \mathbb{E}_t \pi_{t+1}) + \sigma r_t^n \tag{1}$$

$$\pi_t = \kappa x_t + \beta \, \mathbb{E}_t \, \pi_{t+1} + u_t \tag{2}$$

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

#### 2.2 NK model with $\infty$ -horizon forecasts (LR) with learning the constant of $\pi$ only

$$x_t = -\sigma i_t + \hat{\mathbb{E}}_t \sum_{T=t}^{\infty} \beta^{T-t} \left( (1-\beta) x_{T+1} - \sigma(\beta i_{T+1} - \pi_{T+1}) + \sigma r_T^n \right)$$
 (Preston, eq. (18))

$$\pi_t = \kappa x_t + \hat{\mathbb{E}}_t \sum_{T=t}^{\infty} (\alpha \beta)^{T-t} \left( \kappa \alpha \beta x_{T+1} + (1-\alpha) \beta \pi_{T+1} + u_T \right)$$
 (Preston, eq. (19))

$$i_t = \psi_\pi \pi_t + \psi_x x_t + \bar{i}_t$$
 (Preston, eq. (27))

#### 2.3 Anchoring: same as LR, just anchoring instead of decreasing gain

## 3 Compact notation

Exogenous states are summarized as:

$$s_t = Ps_{t-1} + \epsilon_t \quad \text{where} \quad s_t \equiv \begin{pmatrix} r_t^n \\ \bar{i}_t \\ u_t \end{pmatrix} \quad P \equiv \begin{pmatrix} \rho_r & 0 & 0 \\ 0 & \rho_i & 0 \\ 0 & 0 & \rho_u \end{pmatrix} \quad \epsilon_t \equiv \begin{pmatrix} \varepsilon_t^r \\ \varepsilon_t^i \\ \varepsilon_t^i \end{pmatrix} \quad \text{and} \quad \Sigma = \begin{pmatrix} \sigma_r & 0 & 0 \\ 0 & \sigma_i & 0 \\ 0 & 0 & \sigma_u \end{pmatrix}$$

Let  $z_t$  summarize the endogenous variables as

$$z_t \equiv \begin{pmatrix} \pi_t \\ x_t \\ i_t \end{pmatrix} \tag{4}$$

Then I can write the models compactly as

$$z_t = A_p^{RE} \, \mathbb{E}_t \, z_{t+1} + A_s^{RE} s_t \tag{5}$$

$$z_t = A_p^{RE} \hat{\mathbb{E}}_t z_{t+1} + A_s^{RE} s_t \tag{6}$$

$$z_{t} = A_{a}^{LR} f_{a}(t) + A_{b}^{LR} f_{b}(t) + A_{s}^{LR} s_{t}$$
(7)

$$s_t = Ps_{t-1} + \epsilon_t \tag{8}$$

where  $f_a$  and  $f_b$  capture discounted sums of expectations at all horizons of the endogenous states z (following Preston, I refer to these objects as "long-run expectations"):

$$f_a(t) \equiv \hat{\mathbb{E}}_t \sum_{T=t}^{\infty} (\alpha \beta)^{T-t} z_{T+1} \qquad f_b(t) \equiv \hat{\mathbb{E}}_t \sum_{T=t}^{\infty} (\beta)^{T-t} z_{T+1}$$
 (9)

and the coefficient matrices are given by:

$$A_p^{RE} = \begin{pmatrix} \beta + \frac{\kappa \sigma}{w} (1 - \psi_\pi \beta) & \frac{\kappa}{w} & 0 \\ \frac{\sigma}{w} (1 - \psi_\pi \beta) & \frac{1}{w} & 0 \\ \psi_\pi (\beta + \frac{\kappa \sigma}{w} (1 - \psi_\pi \beta)) + \psi_x \frac{\sigma}{w} (1 - \psi_\pi \beta) & \psi_x (\frac{1}{w}) + \psi_\pi (\frac{\kappa}{w}) & 0 \end{pmatrix}$$
(10)

$$\left(\psi_{\pi}\left(\beta + \frac{\kappa \sigma}{w}(1 - \psi_{\pi}\beta)\right) + \psi_{x}\frac{\sigma}{w}(1 - \psi_{\pi}\beta) \quad \psi_{x}(\frac{1}{w}) + \psi_{\pi}(\frac{\kappa}{w}) \quad 0\right)$$

$$A_{s}^{RE} = \begin{pmatrix}
\frac{\kappa \sigma}{w} & -\frac{\kappa \sigma}{w} & 1 - \frac{\kappa \sigma \psi_{\pi}}{w} \\
\frac{\sigma}{w} & -\frac{\sigma}{w} & -\frac{\sigma \psi_{\pi}}{w} \\
\psi_{x}(\frac{\sigma}{w}) + \psi_{\pi}(\frac{\kappa \sigma}{w}) & \psi_{x}(-\frac{\sigma}{w}) + \psi_{\pi}(-\frac{\kappa \sigma}{w}) + 1 & \psi_{x}(-\frac{\sigma \psi_{\pi}}{w}) + \psi_{\pi}(1 - \frac{\kappa \sigma \psi_{\pi}}{w})
\end{pmatrix} \tag{11}$$

$$\begin{pmatrix} \psi_x(\frac{\sigma}{w}) + \psi_\pi(\frac{\kappa\sigma}{w}) & \psi_x(-\frac{\sigma}{w}) + \psi_\pi(-\frac{\kappa\sigma}{w}) + 1 & \psi_x(-\frac{\sigma\psi_\pi}{w}) + \psi_\pi(1 - \frac{\kappa\sigma\psi_\pi}{w}) \end{pmatrix}$$

$$A_a^{LR} = \begin{pmatrix} g_{\pi a} \\ g_{xa} \\ \psi_\pi g_{\pi a} + \psi_x g_{xa} \end{pmatrix} \quad A_b^{LR} = \begin{pmatrix} g_{\pi b} \\ g_{xb} \\ \psi_\pi g_{\pi b} + \psi_x g_{xb} \end{pmatrix} \quad A_s^{LR} = \begin{pmatrix} g_{\pi s} \\ g_{xs} \\ \psi_\pi g_{\pi s} + \psi_x g_{xs} + \begin{bmatrix} 0 & 1 & 0 \end{bmatrix} \end{pmatrix} \quad (12)$$

$$g_{\pi a} = \left(1 - \frac{\kappa \sigma \psi_{\pi}}{w}\right) \left[ (1 - \alpha)\beta, \kappa \alpha \beta, 0 \right] \tag{13}$$

$$g_{xa} = \frac{-\sigma\psi_{\pi}}{w} \left[ (1 - \alpha)\beta, \kappa\alpha\beta, 0 \right] \tag{14}$$

$$g_{\pi b} = \frac{\kappa}{w} \left[ \sigma(1 - \beta \psi_{\pi}), (1 - \beta - \beta \sigma \psi_{x}, 0) \right]$$
(15)

$$g_{xb} = \frac{1}{w} \left[ \sigma(1 - \beta \psi_{\pi}), (1 - \beta - \beta \sigma \psi_{x}, 0) \right]$$

$$\tag{16}$$

$$g_{\pi s} = (1 - \frac{\kappa \sigma \psi_{\pi}}{w}) \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} (I_3 - \alpha \beta P)^{-1} - \frac{\kappa \sigma}{w} \begin{bmatrix} -1 & 1 & 0 \end{bmatrix} (I_3 - \beta P)^{-1}$$
(17)

$$g_{xb} = \frac{1}{w} \left[ \sigma(1 - \beta\psi_{\pi}), (1 - \beta - \beta\sigma\psi_{x}, 0) \right]$$

$$g_{\pi s} = (1 - \frac{\kappa\sigma\psi_{\pi}}{w}) \left[ 0 \quad 0 \quad 1 \right] (I_{3} - \alpha\beta P)^{-1} - \frac{\kappa\sigma}{w} \left[ -1 \quad 1 \quad 0 \right] (I_{3} - \beta P)^{-1}$$

$$g_{xs} = \frac{-\sigma\psi_{\pi}}{w} \left[ 0 \quad 0 \quad 1 \right] (I_{3} - \alpha\beta P)^{-1} - \frac{\sigma}{w} \left[ -1 \quad 1 \quad 0 \right] (I_{3} - \beta P)^{-1}$$

$$(18)$$

$$w = 1 + \sigma \psi_x + \kappa \sigma \psi_\pi \tag{19}$$

## 4 Learning

Use Ryan's timing notation, in which the time index designated the time in which the coefficient is *realized*, which is always one less than the period in which it is *used*. Agents only learn about the constant, and only about the constant of inflation, i.e. about CEMP's drift term, but forecast exogenous states rationally:

$$z_{t} = \begin{bmatrix} \bar{\pi}_{t-2} \\ 0 \\ 0 \end{bmatrix} + bs_{t-1} + \epsilon_{t} \qquad b = gx \ hx$$
 (20)

which is equivalent to saying that their expectations about x and i are rational.

Anticipated utility implies that

$$\hat{\mathbb{E}}_{t-1}\bar{\pi}_{t+h} = \hat{\mathbb{E}}_{t-1}\bar{\pi}_t \equiv \bar{\pi}_{t-1} \quad \forall \ h \ge 0$$
(21)

Agents today mistakenly believe that they will not update the forecasting rule. Moreover, the constant  $\bar{\pi}$  agents will use in period t is the one they updated to in t-1. Assuming RE about the exogenous process and anticipated utility, h-horizon forecasts are constructed as:

$$\hat{\mathbb{E}}_t z_{t+h} = \begin{bmatrix} \bar{\pi}_{t-1} \\ 0 \\ 0 \end{bmatrix} + bP^{h-1} s_t \quad \forall h \ge 1$$
(22)

and the regression coefficient is updated using an RLS algorithm ( $b_1$  is the first row of b):

$$\bar{\pi}_t = \bar{\pi}_{t-1} + k_t^{-1} \underbrace{\left(\pi_t - (\bar{\pi}_{t-1} + b_1 s_{t-1})\right)}_{\text{fcst error using (22)}}$$
(23)

where  $k_t$  is either always  $k_{t-1}+1$  (decreasing gain), or it's described by the CEMP anchoring mechanism:

$$k_t = \mathbb{I} \times \frac{1}{k_{t-1} + 1} + (1 - \mathbb{I}) \times \bar{g}$$
 (24)

$$\mathbb{I} = \begin{cases}
1 & \text{if } \theta_t \le \bar{\theta} \\
0 & \text{otherwise.} 
\end{cases}$$
(25)

$$\theta_t = |\hat{\mathbb{E}}_{t-1}\pi_t - \mathbb{E}_{t-1}\pi_t|/\sigma_s \tag{26}$$

## 5 ALMs

#### 5.1 RE

With some abuse of terminology, call the state-space representation the ALM of the RE model:

$$x_t = hx \ x_{t-1} + \eta e_t \tag{27}$$

$$z_t = gx \ x_t \tag{28}$$

Then I can write the "ALM" as

$$z_t = gx \ hx \ x_{t-1} + gx \ \eta e_t \tag{29}$$

Since this ALM implies no constant, I initialize  $\bar{\pi}_0 = 0$ .

#### 5.2 LR

Evaluate analytical "LR expectations" (9) using the PLM (22):

$$f_a(t) = \frac{1}{1 - \alpha \beta} \bar{z}_{t-1} + b(I_3 - \alpha \beta P)^{-1} s_t \qquad f_b(t) = \frac{1}{1 - \beta} \bar{z}_{t-1} + b(I_3 - \beta P)^{-1} s_t$$
 (30)

## 6 Plan for DW presentation

- 6.1 Contrast LR model w/ and w/o anchoring
- 6.2 Simulations w/ different TR coefficients