Materials 29 - Making an expectations equation residual

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CUSUM-equations:

$$\omega_t = \omega_{t-1} + \kappa k_{t-1}^{-1} (ff' - \omega_{t-1}) \tag{1}$$

$$\theta_t = \theta_{t-1} + \kappa k_{t-1}^{-1} (f' \omega_t^{-1} f - \theta_{t-1})$$
(2)

$$k_t = \mathbb{I}_{\theta_t < \tilde{\theta}}(k_{t-1} + 1) + (1 - \mathbb{I})\bar{g}^{-1}$$
(3)

Instead, I would like to use the smooth anchoring equation because it only adds one extra equation and because the target criterion is formulated in terms of it. But for that I need a functional form that works, i.e. has at least three desirable features and is robust to parameter values and input sequences. Below is one that does an ok job but is very sensitive to parameter values and input sequences:

$$k_t^{-1} = \rho k_{t-1}^{-1} + \gamma f e_{t|t-1}^2 \tag{4}$$

with $\rho=0.5, \gamma=0.01$ (or $\rho=0.9, \gamma=0.001).$ Necessary features:

- 1. generally decreasing
- 2. can jump up from time to time when forecast errors are large
- 3. does not decrease below zero

A Model summary

$$x_{t} = -\sigma i_{t} + \hat{\mathbb{E}}_{t} \sum_{T=t}^{\infty} \beta^{T-t} \left((1-\beta) x_{T+1} - \sigma(\beta i_{T+1} - \pi_{T+1}) + \sigma r_{T}^{n} \right)$$
(A.1)

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

$$i_t = \psi_\pi \pi_t + \psi_x x_t + \bar{i}_t$$
 (if imposed) (A.3)

PLM:
$$\hat{\mathbb{E}}_t z_{t+h} = a_{t-1} + b h_x^{h-1} s_t \quad \forall h \ge 1 \qquad b = g_x h_x$$
 (A.4)

Updating:
$$a_t = a_{t-1} + k_t^{-1} (z_t - (a_{t-1} + bs_{t-1}))$$
 (A.5)

Anchoring function:
$$k_t = k_{t-1} + \mathbf{g}(fe_{t-1}^2)$$
 (A.6)

Forecast error:
$$fe_{t-1} = z_t - (a_{t-1} + bs_{t-1})$$
 (A.7)

LH expectations:
$$f_a(t) = \frac{1}{1 - \alpha \beta} a_{t-1} + b(\mathbb{I}_{nx} - \alpha \beta h)^{-1} s_t$$
 $f_b(t) = \frac{1}{1 - \beta} a_{t-1} + b(\mathbb{I}_{nx} - \beta h)^{-1} s_t$ (A.8)

This notation captures vector learning (z learned) for intercept only. For scalar learning, $a_t = \begin{pmatrix} \bar{a}_t & 0 & 0 \end{pmatrix}'$ and b_1 designates the first row of b. The observables (π, x) are determined as:

$$x_t = -\sigma i_t + \begin{bmatrix} \sigma & 1 - \beta & -\sigma \beta \end{bmatrix} f_b + \sigma \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} (\mathbb{I}_{nx} - \beta h_x)^{-1} s_t$$
 (A.9)

$$\pi_t = \kappa x_t + \begin{bmatrix} (1 - \alpha)\beta & \kappa \alpha \beta & 0 \end{bmatrix} f_a + \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} (\mathbb{I}_{nx} - \alpha \beta h_x)^{-1} s_t$$
 (A.10)

B Target criterion

The target criterion in the simplified model (scalar learning of inflation intercept only, $k_t^{-1} = \mathbf{g}(fe_{t-1})$):

$$\pi_{t} = -\frac{\lambda_{x}}{\kappa} \left\{ x_{t} - \frac{(1-\alpha)\beta}{1-\alpha\beta} \left(k_{t}^{-1} + ((\pi_{t} - \bar{\pi}_{t-1} - b_{1}s_{t-1})) \mathbf{g}_{\pi}(t) \right) \right\}$$

$$\left(\mathbb{E}_{t} \sum_{i=1}^{\infty} x_{t+i} \prod_{j=0}^{i-1} (1 - k_{t+1+j}^{-1} - (\pi_{t+1+j} - \bar{\pi}_{t+j} - b_{1}s_{t+j}) \mathbf{g}_{\bar{\pi}}(t+j)) \right)$$
(B.1)

where I'm using the notation that $\prod_{j=0}^{0} \equiv 1$. For interpretation purposes, let me rewrite this as follows:

$$\pi_{t} = -\frac{\lambda_{x}}{\kappa} x_{t} + \frac{\lambda_{x}}{\kappa} \frac{(1-\alpha)\beta}{1-\alpha\beta} \left(k_{t}^{-1} + f e_{t|t-1}^{eve} \mathbf{g}_{\pi}(t) \right) \mathbb{E}_{t} \sum_{i=1}^{\infty} x_{t+i}$$

$$-\frac{\lambda_{x}}{\kappa} \frac{(1-\alpha)\beta}{1-\alpha\beta} \left(k_{t}^{-1} + f e_{t|t-1}^{eve} \mathbf{g}_{\pi}(t) \right) \left(\mathbb{E}_{t} \sum_{i=1}^{\infty} x_{t+i} \prod_{j=0}^{i-1} (k_{t+1+j}^{-1} + f e_{t+1+j|t+j}^{eve}) \mathbf{g}_{\pi}(t+j) \right)$$
(B.2)

Interpretation: tradeoffs from discretion in RE + effect of current level and change of the gain on future tradeoffs + effect of future expected levels and changes of the gain on future tradeoffs