You know, I don't know about that. <u>16 March 2020</u>

- I wanna pause on i for a sec b/c I can't seem to get it to work and I'm confused about how to get it time-varying anyway. So let's turn to estimation.

Estimation of the anchoring function

The issue is that we wanna estimate the anchoring fct together w/ the model. On the top of my head I can think of 3 ways of doing that:

1) IR-matching
2) Likelihood-based (either MLE or Bayesian)
3) VAR-representation ⇒ exist? est. that!

↳ it would be a time-varying one.

↳ I'm leaning toward #2 b/c 1) it's sexier 2) it's more general than conditional on shocks 3) a TV-VAR sounds challenging

The thing is: 17 March 2020

need to derive the log-likelihood of my model

Take the midsimple model w/ the TR.

In materials 21, this is eq. (5)-(10) + TR

$$\pi_t = \kappa x_t - (1-\alpha)\beta f_a(t) + \left[-\kappa\alpha\beta(I_3-\alpha\beta h_x)^{-1} - e_3(I_3-\alpha\beta h_x)^{-1}\right]s_t$$

$$x_t = -\sigma i_t - \sigma f_b(t) + \left[-(1-\beta)b_2(I_3-\beta h_x)^{-1} + \sigma\beta b_3(I_3-\beta h_x)^{-1} - \sigma e_1(I_3-\beta h_x)^{-1}\right]s_t$$

$$f_a(t) = \frac{1}{1-\alpha\beta}\bar{\pi}_{t-1} - b_1(I_3-\alpha\beta h_x)^{-1}s_t$$

$$f_b(t) = \frac{1}{1-\beta}\bar{\pi}_{t-1} - b_1(I_3-\beta h_x)^{-1}s_t$$

$$\bar{\pi}_t = \bar{\pi}_{t-1} + k_t^{-1}\left(\pi_t - (\bar{\pi}_{t-1} + b_1 s_{t-1})\right)$$

$$k_t^{-1} = k_{t-1}^{-1} + d\left(\pi_t - (\bar{\pi}_{t-1} - b_1 s_{t-1})\right) + c$$

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

This is a state-space model (believe it or not)

and I'm gonna eliminate some variables

$$\pi_t = \kappa x_t - \frac{(1-\alpha)\beta}{1-\alpha\beta}\bar{\pi}_{t-1} - (1-\alpha)\beta b_1(I_3-\alpha\beta h_x)^{-1}s_t$$
$$+ \left[-\kappa\alpha\beta(I_3-\alpha\beta h_x)^{-1} - e_3(I_3-\alpha\beta h_x)^{-1}\right]s_t$$

$$x_t = -\sigma\psi_\pi\pi_t - \sigma\psi_x x_t - \sigma\bar{i}_t - \frac{\sigma}{1-\beta}\bar{\pi}_{t-1} - \sigma b_1(I_3-\beta h_x)^{-1}s_t$$
$$+ \left[-(1-\beta)b_2(I_3-\beta h_x)^{-1} + \sigma\beta b_3(I_3-\beta h_x)^{-1} - \sigma e_1(I_3-\beta h_x)^{-1}\right]s_t$$

$$\pi_t = \kappa x_t - \frac{(1-\alpha)\beta}{1-\alpha\beta}\bar{\pi}_{t-1}$$

$$+ \left[-(1-\alpha)\beta b_1 (I_3 - \alpha\beta h x)^{-1} S_1 - \kappa\alpha\beta (I_3 - \alpha\beta h x)^{-1} - e_3 (I_3 - \alpha\beta h x)^{-1}\right] S_t$$

$$x_t = -\sigma\psi_\pi \pi_t - \sigma\psi_x x_t - \sigma \bar{i}_t - \frac{\sigma}{1-\beta}\bar{\pi}_{t-1} - \sigma b_1 (I_3 - \beta h x)^{-1} S_t$$

$$+ \left[-(1-\beta) b_2 (I_3 - \beta h x)^{-1} + \sigma\beta b_3 (I_3 - \beta h x)^{-1} - \sigma e_1 (I_3 - \beta h x)^{-1}\right] S_t$$

$$(1+\sigma\psi_x) x_t = -\sigma\psi_\pi \pi_t \qquad - \frac{\sigma}{1-\beta}\bar{\pi}_{t-1}$$

$$\left[-\sigma e_2 - \sigma b_1 (I_3 - \beta h x)^{-1} - (1-\beta) b_2 (I_3 - \beta h x)^{-1} + \sigma\beta b_3 (I_3 - \beta h x)^{-1} - \sigma e_1 (I_3 - \beta h x)^{-1}\right] S_t$$

$$\Rightarrow \quad x_t = -\frac{\sigma\psi_\pi}{1+\sigma\psi_x}\pi_t - \frac{1}{1+\sigma\psi_x}\frac{\sigma}{1-\beta}\bar{\pi}_{t-1}$$

$$+ \frac{1}{1+\sigma\psi_x}\left[-\sigma e_2 - \sigma b_1 (I_3 - \beta h x)^{-1} - (1-\beta) b_2 (I_3 - \beta h x)^{-1} + \sigma\beta b_3 (I_3 - \beta h x)^{-1} - \sigma e_1 (I_3 - \beta h x)^{-1}\right] S_t$$

Can even sub x_t out!

$$\pi_t = -\frac{\kappa\sigma\psi_\pi}{1+\sigma\psi_x}\pi_t - \frac{\kappa}{1+\sigma\psi_x}\frac{\sigma}{(1-\beta)}\bar{\pi}_{t-1}$$

$$+ \frac{\kappa}{1+\sigma\psi_x}\left[-\sigma e_2 - \sigma b_1 (I_3 - \beta h x)^{-1} - (1-\beta) b_2 (I_3 - \beta h x)^{-1} + \sigma\beta b_3 (I_3 - \beta h x)^{-1} - \sigma e_1 (I_3 - \beta h x)^{-1}\right] S_t$$

$$- \frac{(1-\alpha)\beta}{1-\alpha\beta}\bar{\pi}_{t-1}$$

$$+ \left[-(1-\alpha)\beta b_1 (I_3 - \alpha\beta h x)^{-1} S_1 - \kappa\alpha\beta (I_3 - \alpha\beta h x)^{-1} - e_3 (I_3 - \alpha\beta h x)^{-1}\right] S_t$$

$$\Leftrightarrow \left(1 + \frac{\kappa\sigma\psi_\pi}{1+\sigma\psi_x}\right)\pi_t = -\left(\frac{\kappa\sigma}{1+\sigma\psi_x(1-\beta)} + \frac{(1-\alpha)\beta}{(1-\alpha\beta)}\right)\bar{\pi}_{t-1} + \text{stuff}\cdot S_t$$

$$\left(1+\frac{k\tilde{b}\psi_\pi}{1+\tilde{b}\psi_x}\right)\pi_t = -\left(\frac{k\tilde{b}}{1+\tilde{b}\psi_x(1-\beta)}+\frac{(1-\alpha)\beta}{(1-\alpha\beta)}\right)\bar{\pi}_{t-1} +$$

$$\left\{\frac{k}{1+\tilde{b}\psi_x}\left[-\tilde{b}e_2-\tilde{b}b_1(f_3-\beta hx)^{-1}-(1-\beta)b_2(f_3-\beta hx)^{-1}+\tilde{b}\beta b_3(f_3-\beta hx)^{-1}-\tilde{b}e_1(f_3-\beta hx)^{-1}\right]\right.$$

$$\left.+\left[-(1-\alpha)\beta b_1(f_3-\alpha\beta hx)^{-1}s_1-k\alpha\beta(f_3-\alpha\beta hx)^{-1}-e_3(f_3-\alpha\beta hx)^{-1}\right]\right\}s_t$$

$$\frac{1+\tilde{b}\psi_x+k\tilde{b}\psi_\pi}{1+\tilde{b}\psi_x}\pi_t = \text{same}$$

$$\Rightarrow \pi_t = -\frac{\cancel{1+\tilde{b}\psi_x}}{1+\tilde{b}\psi_x+k\tilde{b}\psi_\pi}\left(\frac{k\tilde{b}(1-\alpha\beta)+(1-\alpha)\beta(1-\beta)(1+\tilde{b}\psi_x)}{\cancel{(1+\tilde{b}\psi_x)}(1-\beta)(1-\alpha\beta)}\right)\bar{\pi}_{t-1}$$

$$+\left\{\frac{k}{1+\tilde{b}\psi_x+k\tilde{b}\psi_\pi}\left[-\tilde{b}e_2-\tilde{b}b_1(f_3-\beta hx)^{-1}-(1-\beta)b_2(f_3-\beta hx)^{-1}+\tilde{b}\beta b_3(f_3-\beta hx)^{-1}-\tilde{b}e_1(f_3-\beta hx)^{-1}\right]\right.$$

$$\left.+\frac{1+\tilde{b}\psi_x}{1+\tilde{b}\psi_x+k\tilde{b}\psi_\pi}\left[-(1-\alpha)\beta b_1(f_3-\alpha\beta hx)^{-1}s_1-k\alpha\beta(f_3-\alpha\beta hx)^{-1}-e_3(f_3-\alpha\beta hx)^{-1}\right]\right\}\cdot s_t$$

$$\Rightarrow \pi_t = -\frac{k\tilde{b}(1-\alpha\beta)+\beta(1-\alpha)(1-\beta)(1+\tilde{b}\psi_x)}{(1+\tilde{b}\psi_x+k\tilde{b}\psi_\pi)(1-\beta)(1-\alpha\beta)}\bar{\pi}_{t-1} +$$

$$\left\{\frac{k}{1+\tilde{b}\psi_x+k\tilde{b}\psi_\pi}\left[-\tilde{b}e_2-\tilde{b}b_1(f_3-\beta hx)^{-1}-(1-\beta)b_2(f_3-\beta hx)^{-1}+\tilde{b}\beta b_3(f_3-\beta hx)^{-1}-\tilde{b}e_1(f_3-\beta hx)^{-1}\right]\right.$$

$$\left.+\frac{1+\tilde{b}\psi_x}{1+\tilde{b}\psi_x+k\tilde{b}\psi_\pi}\left[-(1-\alpha)\beta b_1(f_3-\alpha\beta hx)^{-1}s_1-k\alpha\beta(f_3-\alpha\beta hx)^{-1}-e_3(f_3-\alpha\beta hx)^{-1}\right]\right\}s_t$$

Damn dam! So we have $\equiv A$

$$\pi_t = -\frac{\kappa\sigma(1-\alpha\beta)+\beta(1-\alpha)(1-\beta)(1+\sigma\psi_x)}{(1+\sigma\psi_x+\kappa\sigma\psi_\pi)(1-\beta)(1-\alpha\beta)}\bar{\pi}_{t-1} \; +$$

$$\Big\{\frac{\kappa}{1+\sigma\psi_x+\kappa\sigma\psi_\pi}\Big[-\sigma e_2-\sigma b_1(I_3-\beta h_x)^{-1}-(1-\beta)b_2(I_3-\beta h_x)^{-1}+\sigma\beta b_3(I_3-\beta h_x)^{-1}-\sigma e_1(I_3-\beta h_x)^{-1}\Big]$$

$$+\frac{1+\sigma\psi_x}{1+\sigma\psi_x+\kappa\sigma\psi_\pi}\Big[-(1-\alpha)\beta b_1(I_3-\alpha\beta h_x)^{-1}s_1-\kappa\alpha\beta(I_3-\alpha\beta h_x)^{-1}-e_3(I_3-\alpha\beta h_x)^{-1}\Big]\Big\}s_t$$

$\equiv B$

$$\bar{\pi}_t = \bar{\pi}_{t-1} + k_t^{-1}\left(\pi_t - (\bar{\pi}_{t-1} + b_1 s_{t-1})\right)$$

$$k_t^{-1} = k_{t-1}^{-1} + d\left(\bar{\pi}_t - (\bar{\pi}_{t-1} - b_1 s_{t-1})\right) + c$$

$\hookrightarrow$ 1 jump (π_t), 3 exog states ($s_t = \begin{bmatrix} r_t^n \\ \bar{i}_t \\ u_t \end{bmatrix}$) and 2 endog states $\xi_t = \begin{bmatrix} \bar{\pi}_t \\ k_t^{-1} \end{bmatrix}$ (or $\begin{bmatrix} \bar{\pi}_{t-1} \\ k_t^{-1} \end{bmatrix}$) so $X_t = \begin{bmatrix} \xi_t \\ s_t \end{bmatrix}$ (states)

$$\pi_t = A\,\bar{\pi}_{t-1} + B\,s_t = \begin{bmatrix} A & B \end{bmatrix}\begin{bmatrix} \xi_t \\ s_t \end{bmatrix}$$

$$\bar{\pi}_t = \bar{\pi}_{t-1} + k_t^{-1}\left(\pi_t - (\bar{\pi}_{t-1} + b_1 s_{t-1})\right)$$

$$k_t^{-1} = k_{t-1}^{-1} + d\Big(\underbrace{\bar{\pi}_t - (\bar{\pi}_{t-1} - b_1 s_{t-1})}_{\text{call this the state(?) } fe_{t-1}}\Big) + c$$

$$\pi_t = A\,\bar{\pi}_{t-1} + B\,s_t \quad = \begin{bmatrix} A & B \end{bmatrix} \begin{bmatrix} \xi_t \\ s_t \end{bmatrix}$$

$$Y_t = gx \cdot X_t$$

$$X_{t+1} = hx\,X_t + \eta\,\varepsilon_t$$

$$\bar{\pi}_t = \bar{\pi}_{t-1} + k_t^{-1}\,fe_{t-1}$$

$$k_t^{-1} = k_{t-1}^{-1} + d \cdot fe_{t-1} + c$$

$$fe_{t-1} = \pi_t - \bar{\pi}_{t-1} - b_1 s_{t-1}$$

several issues y'all:

1) fe state or jump? depends on π_t (a jump)

→ there's gotta be some trick (like π_t in LEMP) to make it a pure state

2.) $\bar{\pi}_t$ nonlinear LOM!

ok - that's troubling. But let's pause it for a sec & let's read what Lütkepohl has to say about MLE & log-likelihoods.

Supp. our VAR(p) looks like

$$y_t - \mu = A_1(y_{t-1} - \mu) + \ldots + A_p(y_{t-p} - \mu) + u_t \quad (3.3.1)$$

p. 75

Then if the VAR(p) is Gaussian, that is

$$u \equiv \mathrm{vec}(U) = \begin{bmatrix} u_1 \\ \vdots \\ u_T \end{bmatrix} \sim N(0, I_T \otimes \Sigma_u) \quad , \text{ which}$$

equivalently means that the prob. density of u is

$$f_u(u) = \frac{1}{(2\pi)^{kT/2}} \left| I_T \otimes \Sigma_u \right|^{-1/2} \exp\left[-\frac{1}{2} u' (I_T \otimes \Sigma_u^{-1}) u \right]$$

then we can use the fact that $u = y - \mu^* - (X' \otimes I_K)\alpha$

where $\underset{k^2 p \times 1}{\alpha := \mathrm{vec}(A)}$, $A := (A_1, \dots, A_p)$ $\quad k \times kp$

$Y^0 := (y_1 - \mu, \dots, y_T - \mu) \qquad k \times T$

$Y_t^0 := \begin{bmatrix} y_t - \mu \\ \vdots \\ y_{t-p+1} - \mu \end{bmatrix} \qquad (kp \times 1)$

$X := (Y_0^0, \dots, Y_{T-1}^0)$,

to write

$$f_y(y) = \left| \frac{\partial u}{\partial y} \right| f_u(u)$$

$$= \frac{1}{(2\pi)^{kT/2}} \left| I_T \otimes \Sigma_u \right|^{-1/2} \exp\left[-\frac{1}{2} \left(y - \mu^* - (X' \otimes I_K)\alpha \right)' (I_T \otimes \Sigma_u^{-1}) \right.$$

$$\left. \cdot \left(y - \mu^* - (X' \otimes I_K)\alpha \right) \right] \quad (3.4.4)$$

and

$$\ln l(\mu, \alpha, \Sigma_u) = -\frac{kT}{2} \ln(2\pi) - \frac{T}{2} \ln|\Sigma_u| - \frac{1}{2} \mathrm{tr}(Y^0 - AX)' \Sigma_u^{-1} (Y^0 - AX)$$

is the log-likelihood. $\quad (3.4.5)$

Given that the updating eq. w/ endog. gain <u>18 March 2020</u>
introduces non-linearities, I'm afraid that even a "simple" & quick estimation has to involve some form of particle filter. But let's see whether Lütkepohl has anything interesting to say about 1) state-space models 2) non-linearities

Lütkepohl, State-space models (Ch. 13, p. 415 ff.)

$$\underset{N\times 1}{z_{t+1}} = \underset{N\times N}{B_t} z_t + \underset{N\times M}{F_t} x_t + \underset{N\times 1}{w_t} \qquad t=0,1,2,\ldots \qquad (13.2.1a)$$

noise

$$\underset{k\times 1}{y_t} = \underset{k\times N}{H_t} z_t + \underset{k\times M}{G_t} \underset{M\times 1}{x_t} + \underset{k\times 1}{v_t} \qquad t=1,2,\ldots \qquad (13.2.2)$$

transition matrix

measurement matrix

input matrixes

inputs/ instruments/ policy vars

measurement error

and $\begin{bmatrix} w_t \\ v_t \end{bmatrix} \sim WN\left[0, VC_t\right]$ $\qquad VC_t = \begin{bmatrix} \Sigma_{w_t} & \Sigma_{w_t v_t} \\ \Sigma_{v_t w_t} & \Sigma_{v_t} \end{bmatrix}$

Nonlinear state-space models

$$z_{t+1} = b_t(z_t, x_t, w_t, \delta_1)$$

$$y_t = h_t(z_t, x_t, v_t, \delta_2)$$

vectors of params

Example of nonlin state-space is the "bilinear" model:

$y_t = \alpha y_{t-1} + u_t + \beta y_{t-1} u_{t-1}$ p. 427 w/ Refs.

↳ $z_{t+1} = B z_t + w_t + C \operatorname{vec}(z_t z_t')$ (13.2.33)

$y_t = [I_K \; 0 \ldots 0] \, z_t$ (13.2.34)

⇒ Bunch of refs on bilinear systems, univariate & multivariate on p. 427 bottom.

MLE of state-space models p. 434

Gather the time-invariant params from $B, F, H_t, G, \Sigma_w, \Sigma_v$ and Σ_0 & μ_0 in δ as

$$\delta = \begin{bmatrix} \operatorname{vec}[v, A_1, \ldots, A_p] \\ \operatorname{vech}(\Sigma_u) \end{bmatrix}$$

where vech = "half-vectorization", $\operatorname{vech}\begin{pmatrix} a & b \\ c & d \end{pmatrix} \equiv \begin{bmatrix} a \\ b \\ d \end{bmatrix}$.

The log-likelihood for the Gaussian state-space model is:

$$\ln l(\delta | y_1, \ldots, y_T) = -\frac{KT}{2} \ln(2\pi) - \frac{1}{2} \sum_{t=1}^{T} \ln |\Sigma_y(t|t-1)|$$
$$- \frac{1}{2} \sum_{t=1}^{T} (y_t - y_{t|t-1})' \Sigma_y(t|t-1)^{-1} (y_t - y_{t|t-1}) \quad (13.4.1)$$

Denoting the fcst error $e_t(\delta) := y_t - y_{t|t-1}$

and $\Sigma_t(\delta) := \Sigma_y(t|t-1)$, we can rewrite this as

$$\ln \ell(\delta) = -\frac{kT}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left[\ln|\Sigma_t(\delta)| + e_t'(\delta)\Sigma_t(\delta)^{-1}e_t(\delta)\right] \quad (13.4.3)$$

which makes explicit

1) the dependence of $\ln \ell$ on δ,

2) that all quantities in the $\ln \ell$ all functions of δ and can (must) be computed using the Kalman filter.

locally identified: when in a subspace of the param space, δ is uniquely determined.

vs. globally identified: when δ is uniquely determined in the entire param space.

↪ identification: we need a min of $-\ln \ell$, so we need some sort of Hessian = pos. def. ⇒ the information matrix, $= E[\text{Hessian}] = E\left[\frac{\partial^2(-\ln \ell)}{\partial\delta\partial\delta}\Big|_{\delta_0}\right]$

A quick note on DSEMs (dynamic simultaneous equations models a.k.a. "linear systems") p. 323

essentially, these are linear VARMAX(p,s,q) models

$$A_0 y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + B_0 x_t + B_1 x_{t-1} + \dots + B_s x_{t-s} + w_t$$

(10.1.1)

- VARMAX(p,s,q) is w_t is MA(q)
- VARX(p,s) if $w_t \sim WN$.

VAR(p) models w/ time-varying coefficients p. 391 ff.

periodic VARs → e.g. w/ seasonal dummies

intervention models → DGP_1 is replaced by DGP_2 at time τ.

$$y_t = v_t + A_{1t} y_{t-1} + \dots + A_{pt} y_{t-p} + u_t \qquad (12.2.1)$$

↳ $WN(0, \Sigma_t)$

also time-varying

(not identically distrib!)

Rewrite the VAR(p) as a VAR(1)

$$Y_t = v_t + A_t Y_{t-1} + U_t \qquad (12.2.2)$$

$$\underset{kp \times 1}{Y_t := \begin{bmatrix} y_t \\ \vdots \\ y_{t-p+1} \end{bmatrix}}, \quad \underset{kp \times 1}{v_t := \begin{bmatrix} v_t \\ 0 \\ \vdots \\ 0 \end{bmatrix}}, \quad \underset{kp \times kp}{A_t := \begin{bmatrix} A_{1t} & \dots & A_{p-1,t} & A_{pt} \\ I_k & \dots & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & \dots & I_k & 0 \end{bmatrix}}, \quad \underset{kp \times 1}{U_t := \begin{bmatrix} u_t \\ 0 \\ \vdots \\ 0 \end{bmatrix}}$$

And by recursive sub we get

$$Y_t = \left[\prod_{j=0}^{h-1} A_{t-j}\right] Y_{t-h} + \sum_{i=0}^{h-1} \left[\prod_{j=0}^{i-1} A_{t-j}\right] v_{t-i} + \sum_{i=0}^{h-1} \left[\prod_{j=0}^{i-1} A_{t-j}\right] U_{t-i} \quad (12.2.3)$$

Defining $J := [I_k \ 0]$ such that $y_t = JY_t$, we can premultiply (12.2.3) by J, define

$\Phi_{it} := J\left[\prod_{j=0}^{i-1} A_{t-j}\right] J'$ to get

$$y_t = \mu_t + \sum_{i=0}^{\infty} \Phi_{it} u_{t-i} \qquad (12.2.6)$$

where $\mu_t = E[y_t]$

$\Rightarrow$ Then the MSE (or FEV of the FE $y_{t+h} - y_t(h)$) is

$$\Sigma_t(h) := \sum_{i=0}^{h-1} \Phi_{i,t+h} \Sigma_{t+h-i} \Phi'_{i,t+h} \qquad (12.2.10)$$

MLE of TV-VAR p. 394

Write (12.2.1) as $y_t = B_t Z_{t-1} + u_t$ (12.2.11)

where $B_t := [\nu_t, A_{1t}, \dots, A_{pt}]$, $Z_{t-1} := (1, Y_{t-1}')'$

B_t depend on the vector $\underset{N\times 1}{\gamma}$ of time-invariant params.

Σ_t depend on $\underset{M\times 1}{\sigma}$ of fixed params.

If $u_t \sim N(0, \Sigma_t)$, the log-likelihood is

$$\ln l(\gamma, \sigma) = -\frac{KT}{2} \ln 2\pi - \frac{1}{2} \sum_{t=1}^{T} \ln |\Sigma_t| - \frac{1}{2} \sum_{t=1}^{T} u_t' \Sigma_t^{-1} u_t$$

(12.2.12)

where initial conditions have been ignored.

You can also derive an info-matrix.

So it seems like you just min $-\ln l(\gamma, \sigma)$!

It also seems like for certain special cases you can even derive the estimators in closed-form!

Ryan meeting 18 March 2020

Not yet convinced that the procedure (param) is sensible

→ the only procedure that can work is

$f_{z,t}$ and more RHS-variables: k^{-1}, $\bar{\pi}$

$$z_t = \bar{z}_t + f_{z,t} z_{t-1} + f_{u,t} u_t$$

things in $f_{z,t}$ will be 0 or simply described by the LOMs

It may be too restrictive.

A computationally intensive exercise is:

- Cong. path for the int. rate (exog.)
- Solve the model for that int. rate
- check the target criterion, compute the resid
- fmincon to min that resid

⇒ find simulated optimal plan.

· Simulate the Ramsey model
· Simulate the model w/ Taylor-rule
⇒ see how close you can get
It might then be that most results won't be pencil & paper.

Comments:

· Concerning w/ linearness of (10)
→ "negative surprises cause me to be unanchored" shouldn't be "big mistakes" → so take the square
↳ like smooth one better than jumpy

· Estim: filter the data → App paper w/ Robert:
match the params to moments cors of data
⇒ would give you results.

They est an NK model: HP-filter both data and model, compute moments and try to match those.