

# Perturbation Methods Extension

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## A Baby Example

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## A Baby Example: A Basic RBC

$$\max_{\{c_t, k_{t+1}\}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \log c_t$$

$$c_t + k_{t+1} = e^{z_t} k_t^\alpha,$$

$$z_{t+1} = \rho z_t + \sigma \varepsilon_{t+1}, \quad \varepsilon_t \sim \mathcal{N}(0, 1).$$

## FOC of this problem

$$\frac{1}{c_t} = \beta \mathbb{E}_t \left[ \frac{1}{c_{t+1}} \left( \alpha e^{\rho z_t + \chi \sigma \varepsilon_{t+1}} k_{t+1}^{\alpha-1} \right) \right]$$
$$c_t + k_{t+1} = e^{z_t} k_t^\alpha,$$

$$z_t = \rho z_{t-1} + \sigma \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, 1).$$

Let  $H(c_t, c_{t+1}, k_t, k_{t+1}, z_{t-1}, z_t)$ , where

$$H_1 = \begin{bmatrix} -1 \\ \frac{1}{c_{ss}^2} \\ 1 \\ 0 \end{bmatrix}, \quad H_2 = \begin{bmatrix} \frac{1}{c_{ss}^2} \\ 0 \\ 0 \end{bmatrix}, \quad H_3 = \begin{bmatrix} 0 \\ -\alpha k_{ss}^{\alpha-1} \\ 0 \end{bmatrix},$$

$$H_4 = \begin{bmatrix} 1-\alpha \\ \frac{1}{k_{ss} c_{ss}} \\ 1 \end{bmatrix}, \quad H_5 = \begin{bmatrix} 0 \\ 0 \\ -\sigma \end{bmatrix}, \quad H_6 = \begin{bmatrix} -\frac{\rho}{c_{ss}} \\ -k_{ss}^\alpha \\ 1 \end{bmatrix}.$$

## Re-parametrization and Taylor

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## A Re-parametrized Policy Function

We search for policy functions

$$c_t = c(k_t, z_{t-1}, \varepsilon_t; \chi).$$

$$c_{t+1} = c(k_{t+1}, z_t, \chi \varepsilon_{t+1}; \chi).$$

$$k_{t+1} = k(k_t, z_{t-1}, \varepsilon_t; \chi).$$

## Taylor's Theorem (assume $\delta = 1$ )

Equilibrium conditions:

$$\begin{aligned} 0 &= \mathbb{E}_t \left[ \frac{1}{c(k_t, z_{t-1}, \varepsilon_t; \chi)} - \beta \frac{\alpha e^{\rho z_t + \chi \sigma \varepsilon_{t+1}} k(k_t, z_{t-1}, \varepsilon_t; \chi)^{\alpha-1}}{c(k(k_t, z_{t-1}, \varepsilon_t; \chi), z_t, \chi \varepsilon_{t+1}; \chi)} \right], \\ 0 &= c(k_t, z_{t-1}, \varepsilon_t; \chi) + k(k_t, z_{t-1}, \varepsilon_t; \chi) - e^{z_t} k_t^\alpha, \\ 0 &= z_t - \rho z_{t-1} - \sigma \varepsilon_t. \end{aligned}$$

This defines  $F(k_t, z_{t-1}, \varepsilon_t; \chi)$ . We will take derivatives w.r.t.  $k_t$ ,  $z_{t-1}$ ,  $\varepsilon_t$  and  $\chi$  and apply Taylor's theorem around the deterministic steady state.

## **Second-Order Approximation**

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## Second-Order Approximation: What changes?

At first order you found (certainty equivalence in this log-utility RBC):

$$c_\chi = 0, \quad k_\chi = 0.$$

At second order, two things happen:

- The policy rules become *curved*: terms like  $c_{kk}$ ,  $c_{kz}$ ,  $c_{zz}$  (and analogously for  $k$ ).
- Risk matters through *even* powers of  $\chi$  (notably  $\chi^2$ ): you get *precautionary* corrections.

Technically: second-order derivatives of the equilibrium map satisfy a *linear* system once first-order objects are known.

## Second-Order Policy Expansions (your parametrization)

Let deviations be

$$\tilde{k}_t := k_t - k_{ss}, \quad \tilde{z}_{t-1} := z_{t-1}, \quad \varepsilon_t \text{ as before.}$$

Second-order Taylor expansions around  $(k_{ss}, 0, 0; \chi = 0)$ :

$$\begin{aligned} c_t = & c_{ss} + c_k \tilde{k}_t + c_z \tilde{z}_{t-1} + c_\varepsilon \varepsilon_t + c_\chi \chi \\ & + \frac{1}{2} \left( c_{kk} \tilde{k}_t^2 + 2c_{kz} \tilde{k}_t \tilde{z}_{t-1} + 2c_{k\varepsilon} \tilde{k}_t \varepsilon_t + 2c_{k\chi} \tilde{k}_t \chi \right. \\ & + c_{zz} \tilde{z}_{t-1}^2 + 2c_{z\varepsilon} \tilde{z}_{t-1} \varepsilon_t + 2c_{z\chi} \tilde{z}_{t-1} \chi \\ & \left. + c_{\varepsilon\varepsilon} \varepsilon_t^2 + 2c_{\varepsilon\chi} \varepsilon_t \chi + c_{\chi\chi} \chi^2 \right), \end{aligned}$$

## Second-Order Conditions (what we set to zero)

Your equilibrium conditions define  $F(k_t, z_{t-1}, \varepsilon_t; \chi) = 0$  for all admissible inputs. Hence, at  $(k_{ss}, 0, 0; 0)$ :

$$F_{xx} = 0 \quad \text{for } x \in \{k, z, \varepsilon, \chi\}.$$

Distinct second-order blocks (Young symmetry applies):

$$F_{kk}, F_{kz}, F_{k\varepsilon}, F_{k\chi}, F_{zz}, F_{z\varepsilon}, F_{z\chi}, F_{\varepsilon\varepsilon}, F_{\varepsilon\chi}, F_{\chi\chi}.$$

Given first-order objects, these equations become *linear* in the second-order coefficients of  $(c, k)$ .

## Unknown second-order coefficients and linear system

Collect second-order coefficients (illustrative ordering):

$$x_2 := (c_{kk}, c_{kz}, c_{zz}, c_{k\varepsilon}, c_{z\varepsilon}, c_{\varepsilon\varepsilon}, c_{\chi\chi}, k_{kk}, k_{kz}, k_{zz}, k_{k\varepsilon}, k_{z\varepsilon}, k_{\varepsilon\varepsilon}, k_{\chi\chi})^\top.$$

Given first-order objects, the second-order conditions can be written as

$$\mathcal{A}_2 x_2 = b_2,$$

where:

- $\mathcal{A}_2$  depends only on steady-state objects and first-order derivatives (and on  $H_u$ ,  $H_{uu}$  at the steady state).
- $b_2$  collects known curvature terms from composing policy rules and the expectations using  $\mathbb{E}[\varepsilon_{t+1}^2] = 1$ .

This is the second-order analogue of your first-order system for  $(c_k, c_z, k_k, k_z)$ .

## Implementation template (chain rule at second order)

Write the equilibrium mapping schematically as

$$F(\cdot) = \mathbb{E}_t H(c_t, c_{t+1}, k_t, k_{t+1}, z_{t-1}, z_t; \chi) + \begin{bmatrix} 0 \\ 0 \\ -\sigma \varepsilon_t \end{bmatrix}.$$

At the steady state, define

$$\Gamma_x := \frac{\partial(c_t, c_{t+1}, k_t, k_{t+1}, z_{t-1}, z_t, \chi)}{\partial x}, \quad x \in \{k, z, \varepsilon, \chi\},$$

and

$$\Gamma_{xy} := \frac{\partial^2(c_t, c_{t+1}, k_t, k_{t+1}, z_{t-1}, z_t, \chi)}{\partial x \partial y}.$$

Then a generic second derivative of  $F$  has the structure

$$F_{xy} = \mathbb{E}_t \left[ H_u \Gamma_{xy} + \Gamma_x^\top H_{uu} \Gamma_y \right],$$

where  $H_u$  is the gradient and  $H_{uu}$  the Hessian of  $H$  w.r.t. its arguments.

## Where does $F_{ab} = \mathbb{E}_t[H_y y_{ab} + y_a^\top H_{yy} y_b]$ come from? (1/2)

Define the equilibrium residual as a composition:

$$F(x) = \mathbb{E}_t[H(y(x))], \quad x = (k, z, \varepsilon, \chi), \quad y = y(x).$$

Notation:

$$\begin{aligned} y_a &:= \frac{\partial y}{\partial a}, & y_{ab} &:= \frac{\partial^2 y}{\partial a \partial b}, \\ H_y &:= \frac{\partial H}{\partial y}, & H_{yy} &:= \frac{\partial^2 H}{\partial y \partial y^\top}. \end{aligned}$$

**Step 1 (first derivative).** Chain rule:

$$F_a = \frac{\partial}{\partial a} \mathbb{E}_t[H(y(x))] = \mathbb{E}_t \left[ \frac{\partial}{\partial a} H(y(x)) \right] = \mathbb{E}_t[H_y y_a].$$

**Step 2 (start second derivative).** Differentiate again and use product rule:

$$F_{ab} = \mathbb{E}_t \left[ \frac{\partial}{\partial b} (H_y y_a) \right] = \mathbb{E}_t[(H_y)_b y_a + H_y y_{ab}].$$

## Where does $F_{ab} = \mathbb{E}_t[H_y y_{ab} + y_a^\top H_{yy} y_b]$ come from? (2/2)

**Step 3 (differentiate  $H_y$ ).** Since  $H_y$  depends on  $x$  only through  $y(x)$ ,

$$(H_y)_b = H_{yy} y_b.$$

Substitute into Step 2:

$$F_{ab} = \mathbb{E}_t[(H_{yy} y_b) y_a + H_y y_{ab}] .$$

Write the first term as a quadratic form (up to row/column conventions):

$$(H_{yy} y_b) y_a = y_a^\top H_{yy} y_b.$$

Therefore,

$$F_{ab} = \mathbb{E}_t \left[ H_y y_{ab} + y_a^\top H_{yy} y_b \right] .$$

*Interpretation:*  $H_y y_{ab}$  captures curvature from the policy mapping  $y(x)$ ;  $y_a^\top H_{yy} y_b$  captures curvature of  $H$  interacting with first-order movements in  $y$ .

## First-order derivatives: compact notation

Define the equilibrium residual after substitution as

$$F(x) = \mathbb{E}_t H(y(x)) + \begin{bmatrix} 0 \\ 0 \\ -\sigma \varepsilon_t \end{bmatrix} \in \mathbb{R}^3, \quad x = (k, z_{t-1}, \varepsilon, \chi).$$

Collect the arguments of  $H$  in

$$y = (c_t, c_{t+1}, k_t, k_{t+1}, z_{t-1}, z_t) \in \mathbb{R}^6.$$

Jacobian (dimensions):

$$H_y := \frac{\partial H}{\partial y} \in \mathbb{R}^{3 \times 6}.$$

At the steady state, write  $H_y$  by columns:

$$H_y = [H_1 \ H_2 \ H_3 \ H_4 \ H_5 \ H_6], \quad H_i \in \mathbb{R}^{3 \times 1}$$

## First-order derivatives: the $k_t$ direction (2/3)

Policy rules:

$$c_t = c(k_t, z_{t-1}, \varepsilon_t; \chi), \quad k_{t+1} = k(k_t, z_{t-1}, \varepsilon_t; \chi), \quad z_t = \rho z_{t-1} + \sigma \varepsilon_t.$$

Derivative of the  $H$ -argument vector w.r.t.  $k_t$ :

$$y_k = \frac{\partial y}{\partial k_t} = \begin{bmatrix} (c_t)_k \\ (c_{t+1})_k \\ (k_t)_k \\ (k_{t+1})_k \\ (z_{t-1})_k \\ (z_t)_k \end{bmatrix} = \begin{bmatrix} c_k \\ c_k k_k \\ 1 \\ k_k \\ 0 \\ 0 \end{bmatrix}, \quad (c_{t+1})_k = c_k (k_{t+1})_k = c_k k_k.$$

Therefore,

$$F_k = H_y y_k = H_1 c_k + H_2(c_k k_k) + H_3 + H_4 k_k.$$

## First-order derivatives: the $z_{t-1}$ direction (3/3)

Derivative of the  $H$ -argument vector w.r.t.  $z_{t-1}$ :

$$y_z = \frac{\partial y}{\partial z_{t-1}} = \begin{bmatrix} (c_t)_z \\ (c_{t+1})_z \\ (k_t)_z \\ (k_{t+1})_z \\ (z_{t-1})_z \\ (z_t)_z \end{bmatrix} = \begin{bmatrix} c_z \\ c_k k_z + c_z \rho \\ 0 \\ k_z \\ 1 \\ \rho \end{bmatrix}, \quad (c_{t+1})_z = c_k k_z + c_z (z_t)_z = c_k k_z + c_z \rho.$$

Therefore,

$$F_z = H_y y_z = H_1 c_z + H_2 (c_k k_z + c_z \rho) + H_4 k_z + H_5 + H_6 \rho.$$

## First-order derivatives: the $\varepsilon_t$ direction

Derivative of the  $H$ -argument vector w.r.t.  $\varepsilon_t$ :

$$y_\varepsilon = \frac{\partial y}{\partial \varepsilon_t} = \begin{bmatrix} (c_t)_\varepsilon \\ (c_{t+1})_\varepsilon \\ (k_t)_\varepsilon \\ (k_{t+1})_\varepsilon \\ (z_{t-1})_\varepsilon \\ (z_t)_\varepsilon \end{bmatrix} = \begin{bmatrix} c_\varepsilon \\ c_k k_\varepsilon + c_z \sigma \\ 0 \\ k_\varepsilon \\ 0 \\ \sigma \end{bmatrix}, \quad (c_{t+1})_\varepsilon = c_k k_\varepsilon + c_z (z_t)_\varepsilon.$$

Equivalently,

$$F_\varepsilon = H_1 c_\varepsilon + H_2(c_k k_\varepsilon + c_z \sigma) + H_4 k_\varepsilon + H_6 \sigma + \begin{bmatrix} 0 \\ 0 \\ -\sigma \end{bmatrix}.$$

## First-order derivatives: the $\sigma$ direction

Derivative of the  $H$ -argument vector w.r.t.  $\sigma$ :

$$y_\sigma = \frac{\partial y}{\partial \sigma} = \begin{bmatrix} (c_t)_\sigma \\ (c_{t+1})_\sigma \\ (k_t)_\sigma \\ (k_{t+1})_\sigma \\ (z_{t-1})_\sigma \\ (z_t)_\sigma \end{bmatrix} = \begin{bmatrix} c_\sigma \\ c_k k_\sigma + c_z \varepsilon_t \\ 0 \\ k_\sigma \\ 0 \\ \varepsilon_t \end{bmatrix}, \quad (c_{t+1})_\sigma = c_k k_\sigma + c_z (z_t)_\sigma.$$

Equivalently,

$$F_\sigma = H_1 c_\sigma + H_2(c_k k_\sigma + c_z \mathbb{E}_t \varepsilon_t) + H_4 k_\sigma + H_6 \mathbb{E}_t \varepsilon_t = H_1 c_\sigma + H_2 c_k k_\sigma + H_4 k_\sigma$$

## The $\chi^2$ block: precautionary terms

Because  $c_\chi = k_\chi = 0$  at first order, mixed terms with a single  $\chi$  typically drop out. The risk correction is pinned down by

$$F_{\chi\chi}(k_{ss}, 0, 0; 0) = 0.$$

This equation is *linear* in  $(c_{\chi\chi}, k_{\chi\chi})$  once the rest of  $x_2$  is solved, and it shifts policies due to uncertainty:

$$c_t \approx c_{ss} + \dots + \frac{1}{2} c_{\chi\chi} \chi^2, \quad k_{t+1} \approx k_{ss} + \dots + \frac{1}{2} k_{\chi\chi} \chi^2.$$

Setting  $\chi = 1$  yields the second-order “risk-adjusted” constants used in simulations.

## Practical recipe to compute the second-order solution

1. Compute steady state  $(k_{ss}, c_{ss})$ .
2. Solve first-order system for  $(c_k, c_z, k_k, k_z)$ .
3. Solve the linear system for  $(c_\varepsilon, k_\varepsilon)$ .
4. Assemble  $\mathcal{A}_2$  and  $b_2$  from the second-order derivative conditions and solve  $\mathcal{A}_2 x_2 = b_2$ .
5. Set  $\chi = 1$  to obtain the second-order approximation for simulations and moments.