Perturbation Methods

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Presentation

We want to solve functional equations of the form

$$F(d(x))=0.$$

where the unknown is d(x). Perturbation solves the problem by using Taylor's theorem and specifying an nth-order approximation

$$d_n(x,\Phi) = \sum_{i=0}^n \Phi_i (x - x_0)^i.$$

We need to find the coefficients $\{\Phi_i\}_i$. How?

Motivation

- Many complicated mathematical problems have either
 - 1. a particular case, or
 - 2. a related problem,

that is easy to solve.

- Often, we can use the solution of the simpler problem as a building block of the general solution.
- This approach has been very successful in physics.

Applications to Economics

- Judd and Guu (1993) showed how to apply perturbation methods to economic problems.
- Recently, these methods have gained popularity; second-order approximations are easy to compute and markedly improve accuracy.
- Perturbation theory generalizes the well-known linearization strategy.
- Sometimes referred to as asymptotic methods.

A Baby Example: A Basic RBC

$$\begin{aligned} \max_{\{c_t, k_{t+1}\}} \ \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \ \log c_t \\ c_t + k_{t+1} &= e^{z_t} k_t^{\alpha} + (1 - \delta) k_t, \\ z_{t+1} &= \rho z_t + \sigma \varepsilon_{t+1}, \ \varepsilon_t \sim \mathcal{N}(0, 1). \end{aligned}$$

FOC of this problem

$$\frac{1}{c_t} = \beta \mathbb{E}_t \left[\frac{1}{c_{t+1}} \left(1 + \alpha e^{z_{t+1}} k_{t+1}^{\alpha - 1} - \delta \right) \right]$$
$$c_t + k_{t+1} = e^{z_t} k_t^{\alpha} + (1 - \delta) k_t,$$
$$z_{t+1} = \rho z_t + \sigma \varepsilon_{t+1}, \ \varepsilon_t \sim \mathcal{N}(0, 1).$$

Main Idea

- Transform the problem by introducing a small perturbation parameter.
- Solve the transformed problem for a particular choice (typically setting the parameter to zero).
- Use that solution to approximate the solution of the original problem.

A Perturbation Approach

- ullet Choose the standard deviation σ as the perturbation parameter.
- Set $\sigma = 0 \Rightarrow$ deterministic model: $z_t = 0$ and $e^{z_t} = 1$.
- The deterministic steady state is straightforward to compute.

A Re-parametrized Policy Function

We search for policy functions

$$c_t = c(k_t, z_t; \sigma).$$

$$k_{t+1} = k(k_t, z_t; \sigma).$$

$$z_{t+1} = z(k_t, z_t) + \sigma \varepsilon_{t+1}.$$

- Note the appearance of the parameter σ .
- We build a local approximation around $\sigma = 0$.

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

Equilibrium conditions:

$$0 = \mathbb{E}_{t} \left[\frac{1}{c(k_{t}, z_{t}; \sigma)} - \beta \frac{\alpha e^{z(k_{t}, z_{t}) + \sigma \varepsilon_{t+1}}, k(k_{t}, z_{t}; \sigma)^{\alpha - 1}}{c(k(k_{t}, z_{t}; \sigma), z(k_{t}, z_{t}) + \sigma \varepsilon_{t+1}; \sigma)} \right],$$

$$0 = c(k_{t}, z_{t}; \sigma) + k(k_{t}, z_{t}; \sigma) - e^{z_{t}} k_{t}^{\alpha}$$

$$0 = z(k_{t}, z_{t}) + \sigma \varepsilon_{t+1} - \rho z_{t} - \sigma \varepsilon_{t+1}.$$

We will take derivatives w.r.t. k_t , z_t , and σ and apply Taylor's theorem around the deterministic steady state. (How to proceed in logs?)

Important Question

Is c(k, 0; 0) different from $c(k, 0; \sigma)$?

Asymptotic Expansion for c_t

Let k be the steady state capital in the deterministic model. Then

$$c_{t} = c(k,0;0) + c_{k}(k,0;0)(k_{t}-k) + c_{z}(k,0;0)z_{t} + c_{\sigma}(k,0;0)\sigma$$

$$+ \frac{1}{2}c_{kk}(k_{t}-k)^{2} + \frac{1}{2}c_{kz}(k_{t}-k)z_{t} + \frac{1}{2}c_{k\sigma}(k_{t}-k)\sigma$$

$$+ \frac{1}{2}c_{zk}z_{t}(k_{t}-k) + \frac{1}{2}c_{zz}z_{t}^{2} + \frac{1}{2}c_{z\sigma}z_{t}\sigma$$

$$+ \frac{1}{2}c_{\sigma k}\sigma(k_{t}-k) + \frac{1}{2}c_{\sigma z}\sigma z_{t} + \frac{1}{2}c_{\sigma \sigma}\sigma^{2} + \cdots$$

Asymptotic Expansion for k_{t+1}

$$k_{t+1} = k(k,0;0) + k_k(k,0;0)(k_t - k) + k_z(k,0;0)z_t + k_\sigma(k,0;0)\sigma$$

$$+ \frac{1}{2}k_{kk}(k_t - k)^2 + \frac{1}{2}k_{kz}(k_t - k)z_t + \frac{1}{2}k_{k\sigma}(k_t - k)\sigma$$

$$+ \frac{1}{2}k_{zk}z_t(k_t - k) + \frac{1}{2}k_{zz}z_t^2 + \frac{1}{2}k_{z\sigma}z_t\sigma$$

$$+ \frac{1}{2}k_{\sigma k}\sigma(k_t - k) + \frac{1}{2}k_{\sigma z}\sigma z_t + \frac{1}{2}k_{\sigma \sigma}\sigma^2 + \cdots$$

Notation

Define the vector of equilibrium conditions as

$$F(k_t, z_t; \sigma) = \mathbb{E}_t \begin{bmatrix} \frac{1}{c(k_t, z_t; \sigma)} - \beta \frac{\alpha e^{\rho z_t + \sigma \varepsilon_{t+1}} k(k_t, z_t; \sigma)^{\alpha - 1}}{c(k(k_t, z_t; \sigma), \rho z_t + \sigma \varepsilon_{t+1}; \sigma)} \\ c(k_t, z_t; \sigma) + k(k_t, z_t; \sigma) - e^{z_t} k_t^{\alpha} \\ c(k_t, z_t) - \rho z_t \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}.$$

Equivalently, write $F(k_t, z_t; \sigma) = \mathbb{E}_t H(c_t, c_{t+1}, k_t, k_{t+1}, z_t, z_{t+1}; \sigma)$, where subscripts H_i denote derivatives w.r.t. the *i*th argument (evaluated at steady state when used below).

Zero-Order Approximation

Evaluate at $(k_t, z_t, \sigma) = (k, 0, 0)$:

$$F(k,0;0)=0.$$

Steady state (for $\delta = 1$):

$$\frac{1}{c} = \beta \alpha(k)^{\alpha-1} \quad \Leftrightarrow \quad 1 = \alpha \beta(k)^{\alpha-1}.$$

Thus

$$k = (\alpha \beta)^{\frac{1}{1-\alpha}}, \qquad c = (\alpha \beta)^{\frac{\alpha}{1-\alpha}} - (\alpha \beta)^{\frac{1}{1-\alpha}}.$$
 (or using the resource constraint)

How good is this approximation?

First-Order Approximation

Take derivatives of $F(k_t, z_t; \sigma)$ and evaluate at (k, 0, 0):

$$F_k(k,0;0) = 0,$$
 $F_z(k,0;0) = 0,$ $F_\sigma(k,0;0) = 0.$

Solving the System I

Recall $F(k_t, z_t; \sigma) =$

$$F(k_t, z_t; \sigma) = \mathbb{E}_t H(c(k_t, z_t; \sigma), c(k(k_t, z_t; \sigma), z(k_t, z_t) + \sigma \varepsilon_{t+1}), k_t, k(k_t, z_t; \sigma), z_t, z(k_t, z_t) + \sigma \varepsilon_{t+1})$$

Since F is identically zero, its derivatives of any order are also zero. Therefore (at the steady state):

$$F_{k} = H_{1}c_{k} + H_{2}(c_{k}k_{k} + c_{z}z_{k}) + H_{3} + H_{4}k_{k} + H_{6}z_{k} = 0,$$

$$F_{z} = H_{1}c_{z} + H_{2}(c_{k}k_{z} + c_{z}z_{z}) + H_{4}k_{z} + H_{5} + H_{6}z_{z} = 0,$$

$$F_{\sigma} = H_{1}c_{\sigma} + H_{2}(c_{k}k_{\sigma} + c_{z}\mathbb{E}\varepsilon_{t+1} + c_{\sigma}) + H_{4}k_{\sigma} + H_{6}\mathbb{E}\varepsilon_{t+1} = 0.$$

Solving the System II

Unknowns at first order: c_k , c_z , k_k , k_z , z_k , z_z , c_σ , k_σ . We have a system to determine them. How to solve it efficiently?

Solving the System II

Note that the pair

$$F_k = 0, \quad F_z = 0$$

constitutes a quadratic system in the four unknowns $(c_k, c_z, k_k, k_z, z_k, z_z)$ and does not depend on (c_σ, k_σ) . Procedures to solve such systems: Blanchard and Kahn (1980),

Uhlig (1999), Sims (2000), Klein (2000) — all equivalent. Why quadratic? Stable vs.

Rewrite as

$$\begin{bmatrix} H_4 & H_6 & H_2 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ c_k & c_z \end{bmatrix} \begin{bmatrix} k_k \\ z_k \end{bmatrix} = - \begin{bmatrix} H_3 & H_5 & H_1 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ c_k \end{bmatrix},$$

$$\begin{bmatrix} H_4 & H_6 & H_2 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ c_k & c_z \end{bmatrix} \begin{bmatrix} k_z \\ z_z \end{bmatrix} = - \begin{bmatrix} H_3 & H_5 & H_1 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ c_z \end{bmatrix}.$$

Or compactly

$$\underbrace{\begin{bmatrix} H_4 & H_6 & H_2 \end{bmatrix}}_{A} \underbrace{\begin{bmatrix} 1 & 0 \\ 0 & 1 \\ c_k & c_z \end{bmatrix}}_{M} \underbrace{\begin{bmatrix} k_k & k_z \\ z_k & z_z \end{bmatrix}}_{h_x} = -\underbrace{\begin{bmatrix} H_3 & H_5 & H_1 \end{bmatrix}}_{B} M.$$

Let
$$h_x = \begin{bmatrix} k_k & k_z \\ z_k & z_z \end{bmatrix}$$
 and unknown vector $\begin{bmatrix} c_k & c_z \end{bmatrix}^\top$.

Let Λ and P be the eigenvalue and eigenvector matrices of h_x :

$$h_{\times}P=P\Lambda$$
.

Then

$$AMP\Lambda = -BMP$$
.

Define

$$Z := MP = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ c_k & c_z \end{bmatrix} P, \qquad A := \begin{bmatrix} H_4 & H_6 & H_2 \end{bmatrix}, \qquad B := -\begin{bmatrix} H_3 & H_5 & H_1 \end{bmatrix}.$$

Then the generalized eigenvalue problem reads

$$AZ \Lambda = BZ$$
.

Generalized Eigenvalue Problem

For given A and B, there exists a matrix $V = [V_1 \ V_2]$ and a block-diagonal $D = \text{diag}(D_{11}, D_{22})$ such that

$$A\begin{bmatrix} V_1 & V_2 \end{bmatrix} \begin{bmatrix} D_{11} & 0 \\ 0 & D_{22} \end{bmatrix} = B\begin{bmatrix} V_1 & V_2 \end{bmatrix}.$$

 D_{11} collects roots with $|\lambda| < 1$.

Stable Roots and Recovery

Assume the number of eigenvalues with $|\lambda| < 1$ equals the number of states. Then set $\Lambda = D_{11}$ and $Z = V_1$:

$$MP = V_1 = \begin{bmatrix} V_{11} \\ V_{21} \end{bmatrix} \quad \Rightarrow \quad P = V_{11}, \qquad \begin{bmatrix} c_k & c_z \end{bmatrix} = V_{21}P^{-1}.$$

Finally,

$$h_{\mathsf{x}} = PD_{11}P^{-1}.$$

Solving the System III

With c_k, c_z, k_k, k_z in hand, determine (c_σ, k_σ) from the linear homogeneous system

$$F_{\sigma} = H_1 c_{\sigma} + H_2 (c_k k_{\sigma} + c_{\sigma}) + H_4 k_{\sigma} = 0 \implies \begin{bmatrix} H_1 + H_2 & H_2 c_k + H_4 \end{bmatrix} \begin{bmatrix} c_{\sigma} \\ k_{\sigma} \end{bmatrix} = 0.$$

Hence

$$c_{\sigma}=k_{\sigma}=0.$$

Interpretation

- Since $c_{\sigma} = k_{\sigma} = 0$, the first-order solution exhibits **certainty equivalence** no precautionary behavior.
- Distinguish *risk aversion* (second derivative of utility) from the *precautionary motive* (third derivative of utility): Leland (1968), Kimball (1990).
- Ignoring numerical error, the *policy* functions have no approximation error at first order; the *value function* still does.

Comparison with Linearization

- After Kydland and Prescott (1982), LQ methods/linearization became popular to solve macro models.
- Properly implemented, linearization, LQ, and first-order perturbation are equivalent.
- Advantages of perturbation: access to higher-order terms with clear theorems.

Second-Order Approximation

Take second derivatives at (k, 0, 0):

$$F_{kk} = 0$$
, $F_{kz} = 0$, $F_{k\sigma} = 0$, $F_{zz} = 0$, $F_{z\sigma} = 0$, $F_{\sigma\sigma} = 0$.

(Remember Young's theorem.)

Solving the Second-Order System

- Substitute known first-order coefficients.
- Obtain a linear system of 12 equations in 12 unknowns.
- Cross terms in $k\sigma$ and $z\sigma$ are zero.
- ullet Conjecture: all terms with odd powers of σ vanish.

Correction for Risk

- A term in σ^2 appears at second order.
- Captures the precautionary motive.
- Certainty equivalence no longer holds.
- Key advantage of going to second order.

Higher-Order Terms

- The recursion can be continued to arbitrarily high order.
- Major advantage: the procedure is recursive.
- Often, a few iterations suffice.
- Accuracy depends on the objective (see Fernández-Villaverde, Rubio-Ramírez, and Santos, 2006).