

# PERTURBATION AND DYNARE

## PERTURBATION

---

Tools for Macroeconomists: The essentials

Petr Sedláček

# Perturbation

---

## PERTURBATION: BASIC IDEA

- Perturbation is a way to approximate a function
  - more generally, it is a way of taking derivatives
  - as such it has broad applications

## PERTURBATION: BASIC IDEA

- Perturbation is a way to approximate a function
  - more generally, it is a way of taking derivatives
  - as such it has broad applications
- it uses Taylor's theorem
- it also uses the Implicit function theorem

# Perturbation

---

THEORETICAL UNDERPINNING

## TAYLOR'S THEOREM

**Theorem** Let  $k \geq 1$  be an integer and let function  $f: \mathbb{R} \rightarrow \mathbb{R}$  be  $k$  times differentiable at point  $a \in \mathbb{R}$ . Then there exists a function  $h_k: \mathbb{R} \rightarrow \mathbb{R}$  such that

$$f(x) = f(a) + f'(a)(x - a) + \frac{f''(a)}{2!}(x - a)^2 + \cdots + \frac{f^{(k)}(a)}{k!}(x - a)^k + h_k(x)(x - a)^k,$$

and  $\lim_{x \rightarrow a} h_k(x) = 0$ .

## IMPLICIT FUNCTION THEOREM

**Theorem** Let  $f: \mathbb{R}^{n+m} \rightarrow \mathbb{R}^m$  be a continuously differentiable function and let  $\mathbb{R}^{n+m}$  have coordinates  $(x, y)$ . Fix a point  $(\bar{x}, \bar{y})$  with  $f(\bar{x}, \bar{y}) = 0$ . If the Jacobian matrix  $\mathcal{J}_{f,y}(\bar{x}, \bar{y})$  is invertible, then there exists an open set  $U$  of  $\mathbb{R}^n$  containing  $\bar{x}$  such that there exists a unique continuously differentiable function  $g: U \rightarrow \mathbb{R}^m$  such that

$$g(\bar{x}) = \bar{y}$$

and

$$f(x, g(x)) = 0 \quad \text{for all } x \in U.$$

Moreover, the partial derivatives of  $g$  in  $U$  are given by the matrix product

$$\frac{\partial g}{\partial x_j}(x) = -[\mathcal{J}_{f,y}(x, g(x))]^{-1} \left[ \frac{\partial f}{\partial x_j}(x, g(x)) \right]$$

# Perturbation

---

DETAILS



## BACK TO THE NEOCLASSICAL MODEL

- the above is all very nice
- but at this point a bit abstract
- lets see if we can write the neoclassical growth model
- in a way that looks like the notation we just used...

## OPTIMALITY CONDITIONS

## OPTIMALITY CONDITIONS

$$c_t^{-\gamma} = \beta \mathbb{E}_t c_{t+1}^{-\gamma} \alpha Z_{t+1} k_{t+1}^{\alpha-1}$$

$$c_t + k_{t+1} = Z_t k_t^\alpha$$

$$Z_t = (1 - \rho) + \rho Z_{t-1} + \sigma \epsilon_t$$

## OPTIMALITY CONDITIONS

$$c_t^{-\gamma} = \beta \mathbb{E}_t c_{t+1}^{-\gamma} \alpha Z_{t+1} k_{t+1}^{\alpha-1}$$

$$c_t + k_{t+1} = Z_t k_t^\alpha$$

$$Z_t = (1 - \rho) + \rho Z_{t-1} + \sigma \epsilon_t$$

- $\sigma$  controls the degree of uncertainty

## WHAT ARE WE AFTER?

- rewrite the above equations as

## WHAT ARE WE AFTER?

- rewrite the above equations as

$$\mathbb{E}_t F[c_{t+1}, c_t, k_{t+1}, Z_{t+1}, k_t, Z_t] = 0$$

## WHAT ARE WE AFTER?

- rewrite the above equations as

$$\mathbb{E}_t F[c_{t+1}, c_t, k_{t+1}, Z_{t+1}, k_t, Z_t] = 0$$

- what are the states ( $x$ ) and “policy” variables ( $g(x)$ )?

## WHAT ARE WE AFTER?

- rewrite the above equations as

$$\mathbb{E}_t F[c_{t+1}, c_t, k_{t+1}, Z_{t+1}, k_t, Z_t] = 0$$

- what are the states ( $x$ ) and “policy” variables ( $g(x)$ )?

$$x_t = [k_t, Z_t]$$



## WHAT ARE WE AFTER?

- rewrite the above equations as

$$\mathbb{E}_t F[c_{t+1}, c_t, k_{t+1}, Z_{t+1}, k_t, Z_t] = 0$$

- what are the states ( $x$ ) and “policy” variables ( $g(x)$ )?

$$x_t = [k_t, Z_t]$$

$$x_{t+1} = h(x_t, \sigma) + \sigma \tilde{\epsilon}_{t+1}$$

## WHAT ARE WE AFTER?

- rewrite the above equations as

$$\mathbb{E}_t F[c_{t+1}, c_t, k_{t+1}, Z_{t+1}, k_t, Z_t] = 0$$

- what are the states ( $x$ ) and “policy” variables ( $g(x)$ )?

$$x_t = [k_t, Z_t]$$

$$x_{t+1} = h(x_t, \sigma) + \sigma \tilde{\epsilon}_{t+1}$$

$$c_t = g(x_t, \sigma)$$

- notice that uncertainty ( $\sigma$ ) explicitly enters the policy function!

## REWRITE THE SYSTEM

## REWRITE THE SYSTEM

$$\mathbb{E}_t F\left(g(h(x_t, \sigma) + \sigma \tilde{\epsilon}_{t+1}, \sigma), g(x_t, \sigma), h(x_t, \sigma) + \sigma \tilde{\epsilon}_{t+1}, x_t\right) = 0$$

# Perturbation

---

1ST ORDER PERTURBATION AND CERTAINTY  
EQUIVALENCE

## PERTURBING THE SYSTEM

- perturbation methods find a local approximation of  $g$  and  $h$

## PERTURBING THE SYSTEM

- perturbation methods find a local approximation of  $g$  and  $h$
- it is local around a certain point  $(\bar{x}, \bar{\sigma})$

## PERTURBING THE SYSTEM

- perturbation methods find a local approximation of  $g$  and  $h$
- it is local around a certain point  $(\bar{x}, \bar{\sigma})$
- in particular, a Taylor approximation around  $(\bar{x}, \bar{\sigma})$  gives



## PERTURBING THE SYSTEM

- perturbation methods find a local approximation of  $g$  and  $h$
- it is local around a certain point  $(\bar{x}, \bar{\sigma})$
- in particular, a Taylor approximation around  $(\bar{x}, \bar{\sigma})$  gives

$$\begin{aligned} g(x, \sigma) \approx & g(\bar{x}, \bar{\sigma}) + g_x(\bar{x}, \bar{\sigma})(x - \bar{x}) + g_\sigma(\bar{x}, \bar{\sigma})(\sigma - \bar{\sigma}) \\ & + 1/2[g_{xx}(\bar{x}, \bar{\sigma})(x - \bar{x})^2 + 2g_{x\sigma}(\bar{x}, \bar{\sigma})(x - \bar{x})(\sigma - \bar{\sigma}) \\ & + g_{\sigma\sigma}(\bar{x}, \bar{\sigma})(\sigma - \bar{\sigma})^2] + \dots \end{aligned}$$

$$\begin{aligned} h(x, \sigma) \approx & h(\bar{x}, \bar{\sigma}) + h_x(\bar{x}, \bar{\sigma})(x - \bar{x}) + h_\sigma(\bar{x}, \bar{\sigma})(\sigma - \bar{\sigma}) \\ & + 1/2[h_{xx}(\bar{x}, \bar{\sigma})(x - \bar{x})^2 + 2h_{x\sigma}(\bar{x}, \bar{\sigma})(x - \bar{x})(\sigma - \bar{\sigma}) \\ & + h_{\sigma\sigma}(\bar{x}, \bar{\sigma})(\sigma - \bar{\sigma})^2] + \dots \end{aligned}$$

## WHAT ARE WE SOLVING FOR?

- we approximate the policy functions with a polynomial

## WHAT ARE WE SOLVING FOR?

- we approximate the policy functions with a polynomial
- the unknown coefficients are the n-order derivatives at  $(\bar{x}, \bar{\sigma})$
- how do we solve for them?

## WHAT ARE WE SOLVING FOR?

- we approximate the policy functions with a polynomial
- the unknown coefficients are the n-order derivatives at  $(\bar{x}, \bar{\sigma})$
- how do we solve for them?
- recall that  $F[x_t, \sigma] = 0$  for any value of  $x$  and  $\sigma$

## WHAT ARE WE SOLVING FOR?

- we approximate the policy functions with a polynomial
- the unknown coefficients are the n-order derivatives at  $(\bar{x}, \bar{\sigma})$
- how do we solve for them?
- recall that  $F[x_t, \sigma] = 0$  for any value of  $x$  and  $\sigma$
- $\rightarrow$  derivatives (of any order) of  $F$  also 0!

$$F_{x^k, \sigma^j}[x_t, \sigma] = 0 \quad \forall x, \sigma, j, k$$

## WHERE ARE WE APPROXIMATING?

- particularly convenient point is the non-stochastic steady state
  - i.e.  $\sigma = 0$  and  $x_t = \bar{x}$

## WHERE ARE WE APPROXIMATING?

- particularly convenient point is the non-stochastic steady state
  - i.e.  $\sigma = 0$  and  $x_t = \bar{x}$
  - $\bar{c} = g(\bar{x}, 0)$  and  $\bar{x} = h(\bar{x}, 0)$

## WHERE ARE WE APPROXIMATING?

- particularly convenient point is the non-stochastic steady state
  - i.e.  $\sigma = 0$  and  $x_t = \bar{x}$
  - $\bar{c} = g(\bar{x}, 0)$  and  $\bar{x} = h(\bar{x}, 0)$
- why is so convenient?
- in principle you can approximate around any point



## GETTING THE POLICY FUNCTION DERIVATIVES

- under 1st order perturbation we have

$$g(x, \sigma) \approx g(\bar{x}, 0) + g_x(\bar{x}, 0)(x - \bar{x}) + g_\sigma(\bar{x}, 0)\sigma$$

$$h(x, \sigma) \approx h(\bar{x}, 0) + h_x(\bar{x}, 0)(x - \bar{x}) + h_\sigma(\bar{x}, 0)\sigma$$

- we also know that

$$g(\bar{x}, 0) = \bar{c}$$

$$h(\bar{x}, 0) = \bar{x}$$

## GETTING THE POLICY FUNCTION DERIVATIVES

- under 1st order perturbation we have

$$g(x, \sigma) \approx g(\bar{x}, 0) + g_x(\bar{x}, 0)(x - \bar{x}) + g_\sigma(\bar{x}, 0)\sigma$$

$$h(x, \sigma) \approx h(\bar{x}, 0) + h_x(\bar{x}, 0)(x - \bar{x}) + h_\sigma(\bar{x}, 0)\sigma$$

- we also know that

$$g(\bar{x}, 0) = \bar{c}$$

$$h(\bar{x}, 0) = \bar{x}$$

- solve for the derivatives (coefficients of approximating Taylor polynomial)

$$F_{x^k, \sigma^j}[x_t, \sigma] = 0 \quad \forall x, \sigma, j, k$$

## DERIVING COEFFICIENTS OF TAYLOR POLYNOMIAL

## DERIVING COEFFICIENTS OF TAYLOR POLYNOMIAL

$$F_x = \frac{\partial F}{\partial x_{t+2}} \frac{\partial x_{t+2}}{\partial x_{t+1}} \frac{\partial x_{t+1}}{\partial x_t} + \frac{\partial F}{\partial x_{t+1}} \frac{\partial x_{t+1}}{\partial x_t} + \frac{\partial F}{\partial x_t}$$

$$= \bar{F}_1 \frac{\partial x_{t+2}}{\partial x_{t+1}} \frac{\partial x_{t+1}}{\partial x_t} + \bar{F}_2 \frac{\partial x_{t+1}}{\partial x_t} + \bar{F}_3$$

$$= \bar{F}_1 h_x^2 + \bar{F}_2 h_x + \bar{F}_3 = 0$$

- $\frac{\partial F(x_{t+2}, x_{t+1}, x_t, \sigma)}{\partial x_{t+i}} \Big|_{x_{t+2}=x_{t+1}=x_t=\bar{x}, \sigma=0} = \bar{F}_{3-i}$
- $\frac{\partial h(x_t, \sigma)}{\partial x_t} \Big|_{x_t=\bar{x}, \sigma=0} \forall t = h_x$

# Perturbation

---

UNCERTAINTY

## CERTAINTY EQUIVALENCE

Certainty equivalence result

# CERTAINTY EQUIVALENCE

## Certainty equivalence result

- the variance of shocks does not matter for policy rules
- important limitation of 1st order approximation

# CERTAINTY EQUIVALENCE

## Certainty equivalence result

- the variance of shocks does not matter for policy rules
- important limitation of 1st order approximation
  - what economic questions cannot be studied in this case?
- what about higher order approximations?



## GETTING 2-ORDER DERIVATIVE W.R.T. $\sigma$

- only  $g_{\sigma\sigma}$  and  $h_{\sigma\sigma}$  matter for policy function
- this affects the constant in the policy rule
- can still have important implications

## GETTING 2-ORDER DERIVATIVE W.R.T. $\sigma$

- only  $g_{\sigma\sigma}$  and  $h_{\sigma\sigma}$  matter for policy function
- this affects the constant in the policy rule
- can still have important implications
  - certain economic questions can be addressed
  - can have indirect effect on dynamics (how?)
- need 3rd order to capture effect of uncertainty on “slopes”

# Perturbation

---

ACCURACY

## LOCAL APPROXIMATION?

- perturbation is also known as local approximation

## LOCAL APPROXIMATION?

- perturbation is also known as local approximation
- when does the question of accuracy arise?

## LOCAL APPROXIMATION?

- perturbation is also known as local approximation
- when does the question of accuracy arise?
- what could go wrong?

## ACCURACY OF PERTURBATION

The theory guarantees local convergence

## ACCURACY OF PERTURBATION

The theory guarantees local convergence

- global convergence *could* be good, but it depends on the approximated function



## ACCURACY OF PERTURBATION

The theory guarantees local convergence

- global convergence *could* be good, but it depends on the approximated function
- e.g. if the true function is analytical  $\rightarrow$  successive approximations converge to truth

## ACCURACY OF PERTURBATION

The theory guarantees local convergence

- global convergence *could* be good, but it depends on the approximated function
- e.g. if the true function is analytical  $\rightarrow$  successive approximations converge to truth

Theory doesn't say anything about convergence properties

## ACCURACY OF PERTURBATION

The theory guarantees local convergence

- global convergence *could* be good, but it depends on the approximated function
- e.g. if the true function is analytical  $\rightarrow$  successive approximations converge to truth

Theory doesn't say anything about convergence properties

- e.g. not clear whether 2nd order is better than 1st

## ACCURACY OF PERTURBATION

The theory guarantees local convergence

- global convergence *could* be good, but it depends on the approximated function
- e.g. if the true function is analytical  $\rightarrow$  successive approximations converge to truth

Theory doesn't say anything about convergence properties

- e.g. not clear whether 2nd order is better than 1st
- nonlinear higher-order polynomials always have “weird” shapes, e.g. [like this](#)
- this can occur close or far away from the steady state!

## ACCURACY OF PERTURBATION

The theory guarantees local convergence

- global convergence *could* be good, but it depends on the approximated function
- e.g. if the true function is analytical  $\rightarrow$  successive approximations converge to truth

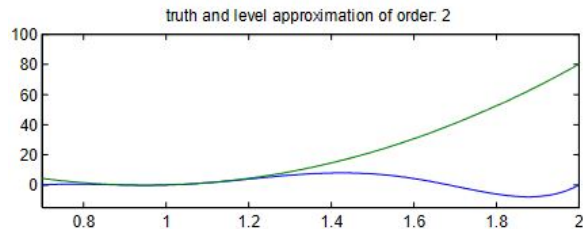
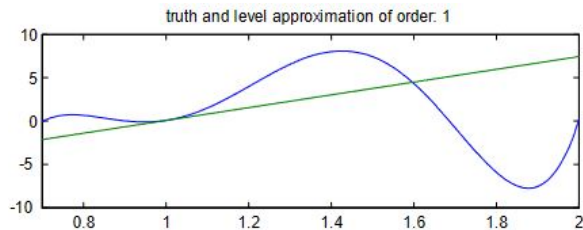
Theory doesn't say anything about convergence properties

- e.g. not clear whether 2nd order is better than 1st
- nonlinear higher-order polynomials always have “weird” shapes, e.g. [like this](#)
- this can occur close or far away from the steady state!

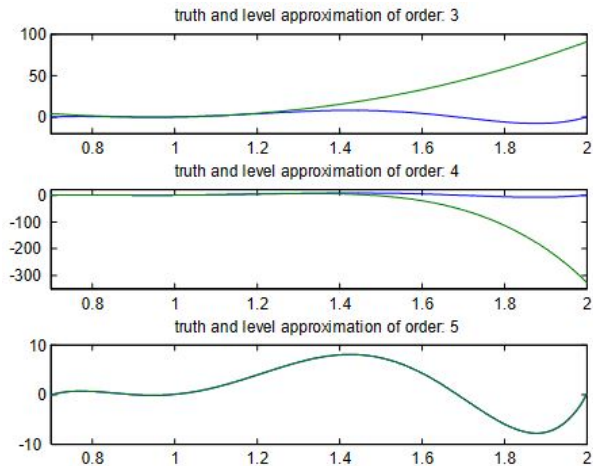
Wouter's example: Consider the true function to be defined on  $x \in [0.7, 2]$  s.t.

$$f(x) = -690.59 + 3202.4x - 5739.45x^2 + 4954.2x^3 - 2053.6x^4 + 327.1x^5$$

## WOUTER'S EXAMPLE: ALL KINDS OF WILD THINGS CAN HAPPEN



## WOUTER'S EXAMPLE: ALL KINDS OF WILD THINGS CAN HAPPEN



# Perturbation

---

TAKING STOCK



## TAKING STOCK

Perturbation:

- (in our context) means of approximating policy rules

## TAKING STOCK

Perturbation:

- (in our context) means of approximating policy rules
- relies on Taylor polynomial and Implicit function theorem

## TAKING STOCK

Perturbation:

- (in our context) means of approximating policy rules
- relies on Taylor polynomial and Implicit function theorem

Pros:

- easy to implement (you'll see)
- can handle large state-space (heterogeneity)

## TAKING STOCK

Perturbation:

- (in our context) means of approximating policy rules
- relies on Taylor polynomial and Implicit function theorem

Pros:

- easy to implement (you'll see)
- can handle large state-space (heterogeneity)

Cons:

- can't handle certain features (non-differentiabilities)

# TAKING STOCK

Perturbation:

- (in our context) means of approximating policy rules
- relies on Taylor polynomial and Implicit function theorem

Pros:

- easy to implement (you'll see)
- can handle large state-space (heterogeneity)

Cons:

- can't handle certain features (non-differentiabilities)
- “local” solution method

