

NLCEQ: Nonlinear Certainty Equivalent Approximation Method

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Deterministic DP model

- ▶ Infinite or finite horizon deterministic dynamic programming problem:

$$V_0(x_0) = \max_{a_t \in \mathcal{D}(x_t)} \sum_{t=0}^{T-1} \beta^t u_t(x_t, a_t) + \beta^T V_T(x_T), \quad (1)$$

s.t. $x_{t+1} = g_t(x_t, a_t),$

- ▶ Standard method to compute value/policy function: value function iteration or time iteration
 - ▶ how to choose appropriate approximation domains
 - ▶ the stability problem
- ▶ New method: NLCEQ (Nonlinear Certainty Equivalent Approximation method)
 - ▶ Cai, Y., K.L. Judd, and J. Steinbuks. A nonlinear certainty equivalent approximation method for dynamic stochastic problems. *Quantitative Economics*.

Basic NLCEQ

Basic NLCEQ

- ▶ Choose approximation method and a corresponding set of approximation nodes $\{x_0^i\}$
 - ▶ Smolyak approximation
 - ▶ Complete polynomials with nodes from monomial rules
 - ▶ Sparse grids, fixed or adaptive
 - ▶ Epsilon-distinguishable sets with L1 approximation methods
- ▶ Data collection step
 - ▶ For each node x_0^i , solve the large-scale optimal control problem to find $v_i = V_0(x_0^i)$ and action a_0^i
 - ▶ Economies of scale
 - ▶ Determine sparsity and use it repeatedly
 - ▶ Compute efficient differentiation code, and use it repeatedly
 - ▶ Collect nodes into clusters, create sequences that warm and hot starts
- ▶ Fitting Step.
 - ▶ Fit $\{(x_0^i, v_i) : 1 \leq i \leq N\}$ to get value function approximation $\hat{V}(x_0; \mathbf{b}_v)$
 - ▶ Fit $\{(x_0^i, a_0^i) : 1 \leq i \leq N\}$ for action a_0 to get policy function approximation $\hat{P}(x_0; \mathbf{b}_a)$
- ▶ Natural Parallelism everywhere

Infinite-Horizon Deterministic DP

- ▶ Infinite-horizon deterministic DP problem:

$$V_0(x_0) = \max_{a_t \in \mathcal{D}(x_t)} \sum_{t=0}^{\infty} \beta^t u_t(x_t, a_t),$$

s.t. $x_{t+1} = g_t(x_t, a_t),$

- ▶ Basic NLCEQ method for infinite-horizon problems
 - ▶ Transform it to a finite-horizon problem
 - ▶ choose a terminal value function which assumes that $x_{t+1} = x_t$ with $t \geq T$
 - ▶ Apply the basic NLCEQ method for the finite-horizon problem

A simple example

- ▶ Solve optimal growth problem:

$$V_0(k_0) = \max_c \sum_{t=0}^{\infty} \beta^t u(c_t),$$
$$\text{s.t. } k_{t+1} = (1 - \delta)k_t + Ak_t^\alpha - c_t,$$

- ▶ Use the basic NLCEQ method: see `growth_NJLCEQ.gms`

NLCEQ Method

- ▶ Stochastic DP problem:

$$V_0(x_0) = \max_{a_t \in \mathcal{D}(x_t)} \mathbb{E} \left\{ \sum_{t=0}^{T-1} \beta^t u_t(x_t, a_t) + \beta^T V_T(x_T) \right\},$$

s.t. $x_{t+1} = g_t(x_t, a_t, \varepsilon_t),$

- ▶ NLCEQ method:

- ▶ Transformation Step: transform stochastic problems to deterministic (and finite-horizon) problems:

$$\tilde{V}_0(x_0) = \max_{a_t \in \mathcal{D}(x_t)} \sum_{t=0}^{T-1} \beta^t u_t(x_t, a_t) + \beta^T \tilde{V}_T(x_T),$$

s.t. $x_{t+1} = g_t(x_t, a_t)$

- ▶ Apply the basic NLCEQ method for the finite-horizon deterministic problem

Comparison with Other Methods

- ▶ Perturbation methods
 - ▶ only valid for non-evolving infinite-horizon models
 - ▶ local approximation
 - ▶ does not work for problems with occasionally binding inequality constraints
- ▶ Projection methods
 - ▶ only valid for non-evolving infinite-horizon models
 - ▶ Challenging for high-dimensional problems
 - ▶ Challenging for problems with occasionally binding inequality constraints
- ▶ Value function iteration and/or time iteration
 - ▶ Challenging for high-dimensional problems
 - ▶ Challenging for problems with occasionally binding inequality constraints
 - ▶ iteration may be unstable (approximation domains, shape-preservation)
 - ▶ accumulated errors from numerical approximation, integration and optimization could be large

Multi-country optimal growth problem

- ▶ N -country optimal growth problem

$$\max_{c, \ell, I} \mathbb{E} \left(\sum_{t=0}^{\infty} \beta^t U(c_t, \ell_t) \right)$$

subject to

$$K_{t+1,j} = (1 - \delta)K_{t,j} + I_{t,j}$$

$$\ln(\theta_{t+1,j}) = \rho \ln(\theta_{t,j}) + \sigma(\epsilon_{t+1,j} + \epsilon_{t+1})$$

$$\sum_{j=1}^N (c_{t,j} + I_{t,j} - \delta K_{t,j}) = \sum_{j=1}^N (\theta_{t,j} f(K_{t,j}, \ell_{t,j}) - \Gamma_{t,j})$$

► with

$$f(K_{t,j}, l_{t,j}) = A(K_{t,j})^\alpha (l_{t,j})^{1-\alpha}$$

$$\Gamma_{t,j} \equiv \frac{\phi}{2} K_{t,j} \left(\frac{l_{t,j}}{K_{t,j}} - \delta \right)^2$$

$$U(c_t, l_t) = \sum_{j=1}^N \tau_j u_j(c_{t,j}, l_{t,j})$$

$$u_j(c_{t,j}, l_{t,j}) = \frac{(c_{t,j})^{1-\frac{1}{\gamma_j}}}{1-\frac{1}{\gamma_j}} - B_j \frac{(l_{t,j})^{1+\frac{1}{\eta_j}}}{1+\frac{1}{\eta_j}}$$

Errors

- ▶ Euler Errors (unit-free):

$$E_1(K, \theta) = \max_{1 \leq j \leq N} |\mathbb{E} \{F_j(K, \theta, \theta^+)\} - 1|$$

with

$$F_j(K, \theta, \theta^+) \equiv \frac{\beta \frac{\partial u_j}{\partial c}(c_j^+, l_j^+)}{\frac{\partial u_j}{\partial c}(c_j, l_j)} \omega_j \left[\pi_j^+ + \theta_j^+ \frac{\partial f}{\partial K}(K_j^+, l_j^+) \right]$$

- ▶ Other Errors:

$$E_2(K, \theta) = \max_{2 \leq j \leq N} \left| \frac{\frac{\partial u_j}{\partial c}(c_j, l_j) \tau_j}{\frac{\partial u_1}{\partial c}(c_1, l_1) \tau_1} - 1 \right|$$

$$E_3(K, \theta) = \max_{1 \leq j \leq N} \left| \frac{\frac{\partial u_j}{\partial c}(c_j, l_j) \theta_j \frac{\partial f}{\partial \ell}(K_j, l_j)}{\frac{\partial u_j}{\partial \ell}(c_j, l_j)} + 1 \right|$$

$$E_4(K, \theta) = \left| \frac{\sum_{j=1}^N (c_j + l_j - \delta K_j + \Gamma_j)}{\sum_{j=1}^N (\theta_j f(K_j, l_j))} - 1 \right|$$

Results for Low-Dimensional Problems

- ▶ Results of NLCEQ for 2-country problems
- ▶ Use degree- n complete Chebyshev polynomials for approximation
- ▶ See growth4D_NLCEQ.gms
- ▶ Use true solutions from value function iteration to estimate the errors

β	γ	η	Global Error \mathcal{E}			
			degree- D Chebyshev		level- l Smolyak	
			$D = 2$	$D = 4$	$l = 1$	$l = 2$
0.99	0.25	0.1	2.4(-2)	1.7(-3)	5.3(-2)	6.7(-3)
		0.5	2.1(-2)	2.0(-3)	6.5(-2)	1.0(-2)
	0.5	0.1	2.0(-2)	1.3(-3)	6.1(-2)	5.3(-3)
		0.5	2.1(-2)	1.1(-3)	6.5(-2)	6.1(-3)
0.95	0.25	0.1	2.8(-2)	2.6(-3)	5.1(-2)	9.3(-3)
		0.5	1.8(-2)	3.7(-3)	7.0(-2)	1.3(-2)
	0.5	0.1	2.0(-2)	1.5(-3)	5.7(-2)	5.6(-3)
		0.5	1.5(-2)	1.7(-3)	6.2(-2)	8.7(-3)

Results for High-Dimensional Problems

- ▶ Results of NLCEQ for high-dimensional N -country problems ($2N$ dimensional)
- ▶ Use level- n Smolyak grid and Chebyshev-Smolyak polynomial approximation (degree 2^n)
- ▶ Parallelization in optimization step
- ▶ Errors and running times:

N	Level l	Num of Points	Num of Cores	T	Max Euler Error	Global Error	Time (minutes)
50	1	201	201	20	2.3(-3)	1.8(-2)	0.8
	2	20,201	2,048	20	1.5(-3)	2.7(-3)	8.3
			20,201	50	3.5(-4)	2.6(-3)	8.6
100	1	401	401	20	1.9(-3)	1.8(-2)	2.2
200	1	801	801	20	1.6(-3)	1.8(-2)	8.0

Note: $a(-n)$ represents $a \times 10^{-n}$.

RBC with investment constraint

- ▶ The RBC model

$$\max_c \mathbb{E} \left\{ \sum_{t=0}^{\infty} \beta^t U(c_t) \right\}$$

subject to

$$c_t + I_t = A_t k_t^\alpha,$$

$$k_{t+1} = (1 - \delta)k_t + I_t,$$

$$I_t \geq \phi I_{SS},$$

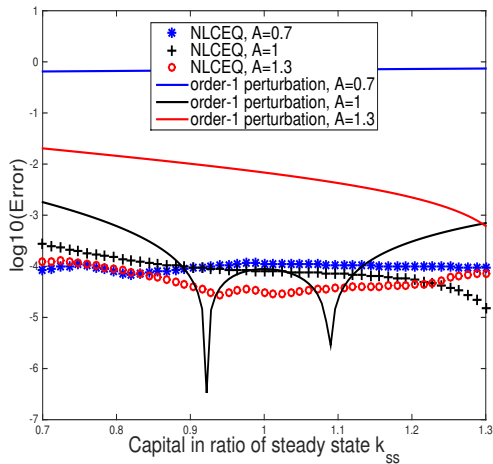
- ▶ Technology A_t :

$$\ln(A_{t+1}) = \rho \ln(A_t) + \sigma \epsilon_{t+1},$$

- ▶ See `growth_bind_NLCEQ.gms`

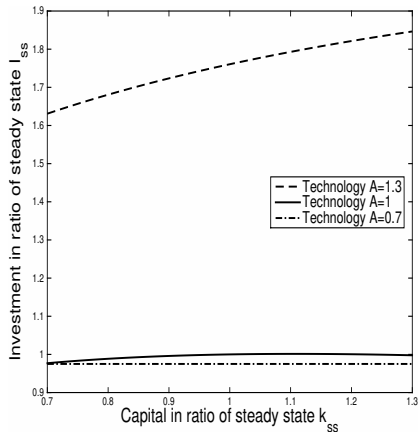
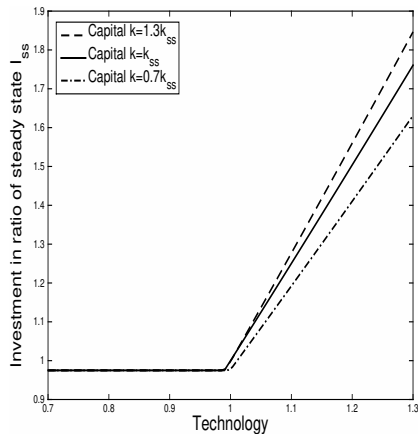
Results

Figure: Errors of the solutions from NLCEQ or log-linearization for the RBC model with a constraint on investment



Results

Figure: Investment policy function for the RBC model with a constraint on investment



NLCEQ with Discrete Stochastic States

- ▶ Discrete stochastic state θ_t
 - ▶ an exogenous Markov chain with k possible values, $\{\vartheta_1, \dots, \vartheta_k\}$
 - ▶ transition matrix P
- ▶ If the initial-time state $\theta_0 = \vartheta_i$, then unconditional probability vector at time t is: $p_{t,i} = P^t \mathbf{e}_i$
- ▶ In the transformation step of NLCEQ, replace θ_t by $\sum_{j=1}^k p_{t,i,j} \vartheta_j$ for an initial $\theta_0 = \vartheta_i$

NLCEQ Method for Competitive Equilibrium

- ▶ Equations for equilibrium (Euler equations, transition laws of states; market clearing conditions; other first-order conditions)

$$\mathbf{F}(\mathbf{x}_t, \mathbf{a}_t, \mathbf{x}_{t+1}, \mathbf{a}_{t+1}) = 0, \quad t = 0, 1, 2, \dots$$

- ▶ State and control variables converge to steady values

$$\mathbf{x}_\infty = \mathbf{x}_{ss}, \quad \mathbf{a}_\infty = \mathbf{a}_{ss}.$$

- ▶ Optimization method for competitive equilibrium:

$$\begin{aligned} \min_{\mathbf{a}_t \in \mathcal{D}(\mathbf{x}_t)} \quad & \|\mathbf{x}_T^{\text{Endo}} - \mathbf{x}_{ss}^{\text{Endo}}\| + \|\mathbf{a}_T - \mathbf{a}_{ss}\| \\ \text{s.t.} \quad & \mathbf{F}(\mathbf{x}_t, \mathbf{a}_t, \mathbf{x}_{t+1}, \mathbf{a}_{t+1}) = 0, \quad t = 0, 1, \dots, T-1, \\ & \mathbf{x}_0 = \mathbf{x}_0^j, \end{aligned}$$

New Keynesian Model with Zero Lower Bound

The New Keynesian model: a representative household, a government, a final-good firm, and intermediate firms

- ▶ The representative household

$$\max_{c_t, \ell_t, b_t} \mathbb{E} \left\{ \sum_{t=0}^{\infty} \left(\prod_{i=0}^t \beta_i \right) U(c_t, \ell_t) \right\}$$

subject to

$$p_t c_t + \frac{b_t}{1 + r_t} = w_t \ell_t + b_{t-1} + T_t + \Pi_t$$

- ▶ b_t : bond face value
- ▶ p_t : price of consumption c_t from the production of the final-good firm
- ▶ T_t : lump sum transfer from the government
- ▶ Π_t : profit from all firms

Specifications

- ▶ Stochastic discount factor β_t :

$$\ln(\beta_{t+1}) = (1 - \rho) \ln(\beta^*) + \rho \ln(\beta_t) + \sigma \epsilon_{t+1}$$

- ▶ Utility

$$U(c, \ell) = \ln(c) - \frac{\ell^{1+\eta}}{1+\eta}$$

- ▶ Final-good firm

$$\max_{y_{i,t}} p_t y_t - \int_0^1 p_{i,t} y_{i,t} di$$

with

$$y_t = \left(\int_0^1 y_{i,t}^{\frac{\alpha-1}{\alpha}} di \right)^{\frac{\alpha}{\alpha-1}}$$

Specifications

- ▶ Intermediate firms: production $y_{i,t+j} = \ell_{i,t+j}$
 - ▶ Calvo-type prices: a fraction $1 - \theta$ of the firms have optimal prices and the remaining fraction θ of the firms keep the same price as in the previous period.
 - ▶ A re-optimizing intermediate firm $i \in [0, 1]$ chooses its price $p_{i,t}$ to maximize the current value of profit over the time when the optimal $p_{i,t}$ remains effective:

$$\max_{p_{i,t}} \mathbb{E}_t \left\{ \sum_{j=0}^{\infty} \left(\prod_{k=0}^j \beta_{t+k} \right) \lambda_{t+j} \theta^j (p_{i,t} y_{i,t+j} - w_{t+j} \ell_{i,t+j}) \right\}$$

- ▶ λ_t : the Lagrange multiplier of the budget constraint

Prices, labor, and government spending

- ▶ price

$$\begin{aligned} p_t &= \left(\int_0^1 p_{i,t}^{1-\alpha} di \right)^{\frac{1}{1-\alpha}} \\ &= \left((1-\theta)(q_t p_t)^{1-\alpha} + \theta \int_0^1 p_{i,t-1}^{1-\alpha} di \right)^{\frac{1}{1-\alpha}} \\ &= \left((1-\theta)(q_t p_t)^{1-\alpha} + \theta p_{t-1}^{1-\alpha} \right)^{\frac{1}{1-\alpha}} \end{aligned}$$

- ▶ labor

$$l_t = \int_0^1 l_{i,t} di,$$

- ▶ Government: spend $g_t = s_g y_t$; issue bonds and pay dividends; lump sum transfer

Equilibrium

- ▶ Euler equation

$$1 = \mathbb{E}_t \left\{ \beta_{t+1} \frac{1 + r_t}{\pi_{t+1}} \frac{c_t}{c_{t+1}} \right\}$$

- ▶ Zero Lower Bound (ZLB) for nominal interest rates r_t

$$r_t = \max(z_t, 0)$$

with

$$z_t = (1 + r^*) \left(\frac{\pi_t}{\pi^*} \right)^{\phi_\pi} \left(\frac{y_t}{y^*} \right)^{\phi_y} - 1 \quad (2)$$

► Other equilibrium equations

$$1 = \frac{1}{\chi_{t,1}} \left(y_t \ell_t^\eta + \theta \mathbb{E}_t \{ \beta_{t+1} \pi_{t+1}^\alpha \chi_{t+1,1} \} \right)$$

$$1 = \frac{1}{\chi_{t,2}} \left(\frac{y_t}{c_t} + \theta \mathbb{E}_t \{ \beta_{t+1} \pi_{t+1}^{\alpha-1} \chi_{t+1,2} \} \right)$$

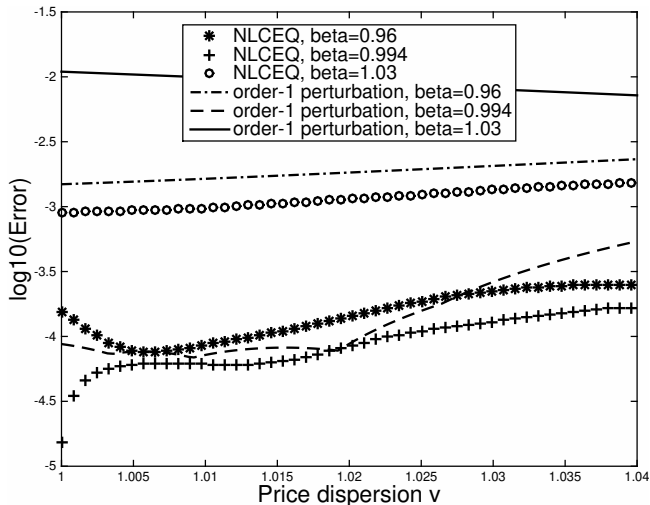
$$q_t = \frac{\alpha \chi_{t,1}}{(\alpha - 1) \chi_{t,2}} = \left(\frac{1 - \theta \pi_t^{\alpha-1}}{1 - \theta} \right)^{\frac{1}{1-\alpha}}$$

$$v_{t+1} = \frac{\ell_t}{y_t} = (1 - \theta) q_t^{-\alpha} + \theta \pi_t^\alpha v_t$$

- State variables: β_t and v_t
- Find policy functions $(c_t, \chi_{t,1}, \chi_{t,2}, \pi_t, q_t, v_t, \ell_t, y_t, r_t, z_t)$: see newKeynesian_NLCEQ.gms

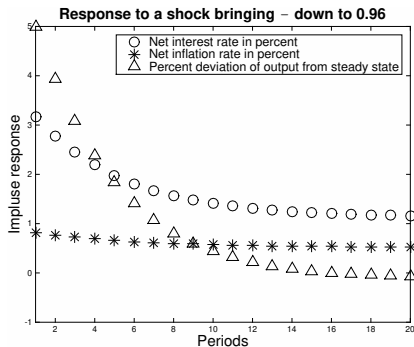
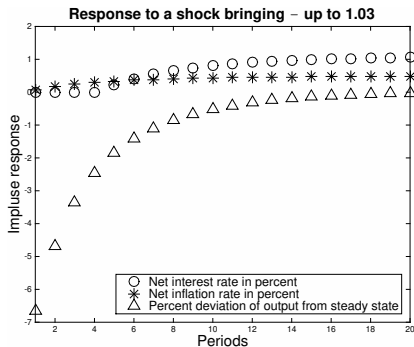
Results: Errors

Figure: Errors of the NLCEQ solution for the New Keynesian DSGE model with ZLB



Results: Impulse response to discount factor shock

Figure: Impulse responses to a shock of discount factor



Summary

- ▶ NLCEQ is a simple method
- ▶ NLCEQ is easy for coding
- ▶ NLCEQ is stable and robust even for problems with kinks
- ▶ NLCEQ is more accurate than log-linearization
- ▶ NLCEQ can deal with high-dimensional dynamic stochastic problems
 - ▶ efficient and natural parallelism
 - ▶ hundreds of dimensions (so far, thousands in the future)
 - ▶ compatible with all approximation methods
- ▶ NLCEQ can solve both social planners' problems and competitive equilibrium