

Macroeconomics, PhD core

Lecture #8

Julieta Caunedo

- ▶ Computation incomplete markets economy
 - ▶ Collocation (today)
 - ▶ Endogenous grid method (an alternative in Carroll, 2006)
- ▶ Uses of compecon

`https://pfackler.wordpress.ncsu.edu/compecon/154-2/`

Based on R. Guntin's notes... based on Gianluca V. and Virgiliu M. at NYU

Application: Incomplete Markets Model

We want to solve

$$V(a, \epsilon) = \max_{a', \tilde{c} \geq 0} u(\tilde{c}) + \beta \mathbb{E} \left[V(a', \epsilon') \right]$$

subject to

$$\tilde{c} + a' = w\epsilon + (1+r)a$$

$$a' \geq \underline{a}$$

$$\epsilon' = \rho\epsilon + \varepsilon$$

$$\varepsilon \sim iid$$

- solve using collocation method $\rightarrow V(a, \epsilon) \approx B(a, \epsilon)c$
where B are basis functions and c are “collocation” coefficients

Function approximation

- ▶ Objective is to find \hat{f} such that it minimizes

$$\|f - \hat{f}\|_{\infty} = \sup_{x \in D} |f(x) - \hat{f}(x)|$$

- ▶ Function interpolation
 - ▶ $\hat{f}(x, c)$ linear combination of polynomials with coefficients c
 - ▶ choose c to minimize $|f - \hat{f}|$ at finite number of nodes
 - ▶ Key: choice of polynomial and nodes

Choice of polynomial and nodes

Choose basis functions $b_1(x), \dots, b_n(x)$

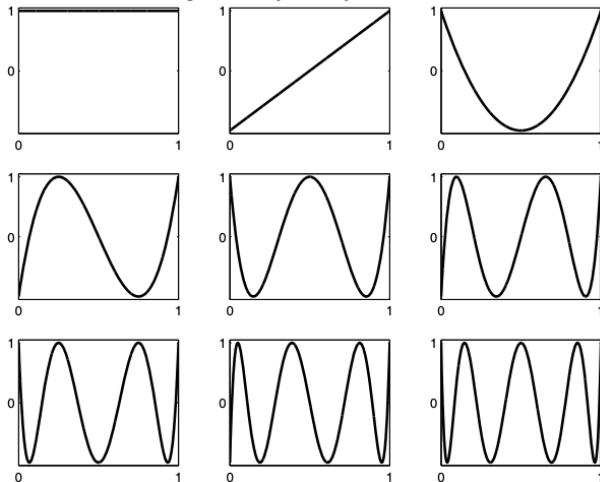
- ▶ $b_n(x) = x^n$ typically bad idea
- ▶ Chebyshev orthogonal polynomials
- ▶ Splines k-th order polynomials spliced together (linear popular choice)

Choose nodes $x = x_1, \dots, x_n$

- ▶ Equidistant typically bad
- ▶ Chebyshev nodes (roots of n-th degree Chebyshev polynomial) optimal
- ▶ use function `funnode`

Chebyshev basis functions: b_i

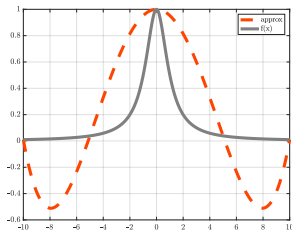
Figure 3: Chebyshev Polynomial Basis Functions



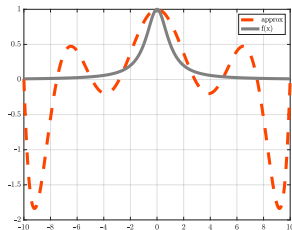
Approximating Function Example: $1/(1+x^2)$

► Chebyshev basis and equidistant nodes

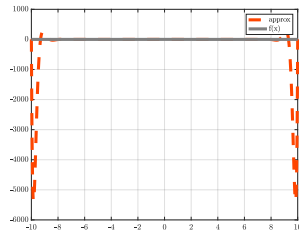
$n = 5$



$n = 9$



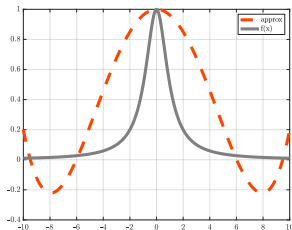
$n = 30$



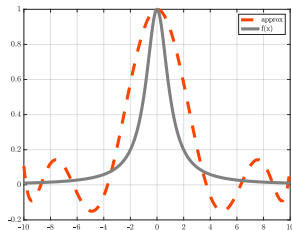
Approximating Function Example: $1/(1+x^2)$

► Chebyshev basis and Chebyshev nodes

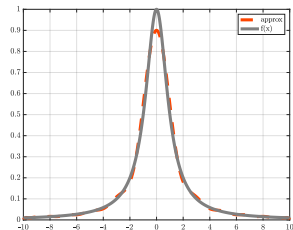
$n = 5$



$n = 9$

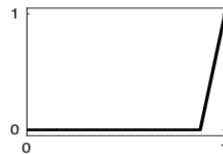
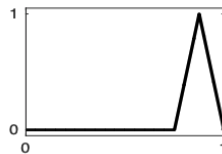


$n = 30$



Splines basis functions: b_i

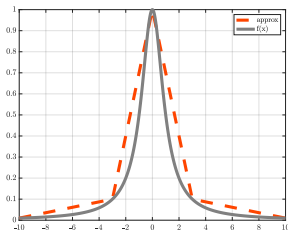
Linear Spline Basis Functions



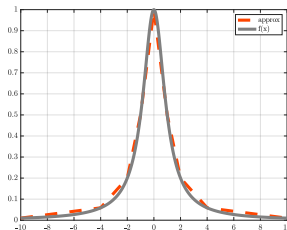
Approximating Function Example: $1/(1+x^2)$

- Splines (linear) basis and n break points

$n = 5$



$n = 9$



- Splines can be non-linear (e.g., cubic)

Computation

1. Choose n order of polynomial
2. Choose $m \geq n$ nodes
3. Evaluate at nodes $B(x)$ where

$$B(x) = \begin{bmatrix} b_1(x_1) & b_2(x_1) & \dots & b_n(x_1) \\ b_1(x_2) & b_2(x_2) & \dots & b_n(x_2) \\ \vdots & \vdots & \dots & \vdots \\ b_1(x_m) & b_2(x_m) & \dots & b_n(x_m) \end{bmatrix}$$

4. Find c using $F = Bc$ then compute $c = B \backslash F$ (F also evaluated at x)

Example: Code using Splines

► Matlab code

```
a = -10;  
b = 10;  
xnode = (a:.001:b)';  
  
break_points = [-10; -3; 0; 3 ; 10];  
fspace = fundef({'spli', break_points,0,1}); % linear splines  
s = funnode(fspace); % nodes  
Phi = funbas(fspace, s); % evaluate n by n matrix of n basis functions at n points in s  
  
F = 1./(1+s.^ 2);  
c = Phi \ F;  
  
Phinode = funbas(fspace, xnode); % basis functions at xnode  
plot(xnode,Phinode*c) % plot approximation
```

More than 1 dimension

- ▶ Goal: approximate $f(x, y)$
- ▶ Generate x and y nodes
- ▶ Basis functions b_i^x and b_j^y
- ▶ Approximate

$$F = \sum_i^{n_x} \sum_j^{n_y} b_i^x(x) b_j^y(y) c_{ij}$$

- ▶ find c with $c = B \setminus F$ where $B = B_d \otimes B_{d-1} \dots \otimes B_1$

Example: $1/(1 + x^2y^2)$

► Matlab code

```
n=[7,7]; % nodes in each dimension
a=[-10,-10]; b=[10,10]; % bounds in each dimension

fspace=fundefn('cheb',n,a,b) % define func. approx. space
xnode=funnode(fspace); % default nodes
xnode=gridmake(xnode); % Cartesian product of univariate nodes
Phi=funbas(fspace,xnode,[0, 0]); % basis function at Cartesian product

F=1./(1+xnode(:,1).^2.*xnode(:,2).^2); %eval. function at nodes
c = Phi \ F;
```

Application: Incomplete Markets Model

We want to solve

$$V(a, \epsilon) = \max_{a', \tilde{c} \geq 0} u(\tilde{c}) + \beta \mathbb{E} [V(a', \epsilon')]$$

subject to

$$\tilde{c} + a' = w\epsilon + (1+r)a$$

$$a' \geq \underline{a}$$

$$\epsilon' = \rho\epsilon + \varepsilon$$

$$\varepsilon \sim iid$$

- ▶ Discretize shock process
- ▶ solve using collocation method $\rightarrow V(a, \epsilon) \approx B(a, \epsilon)c$

Markov Transition Probability: Discretization

- ▶ Discretize process: $e' = \rho e + \epsilon$
 - ▶ Commonly used Tauchen, Rouwenhorst
 - ▶ Using Compecon: example, assume $\sim^{\text{iid}} N(0, \sigma_e^2)$
<https://pfackler.wordpress.ncsu.edu/compecon/154-2/>
 1. `[epse, we] = qnwnorm(n_points, 0, sde^2); %discretize normal distribution`
 2. `fspace = fundef({'spli', egrid, 0, 3}); s = funnode(fspace); Ns = size(s, 1);`
 3. Compute e'

```
for j = 1 : numel(epse)
    eprime = rhoe*s + p.epse(j);
    eprime = max(min(eprime, p.emax), p.emin); % Replace for bounds
end
```
- or quantecon
https://python.quantecon.org/finite_markov.html

Application: Incomplete Markets Model

Broad steps

1. Parameters and grid
2. Define space (e.g., B and B^E)
 - Notice that B^E can be computed using B and !

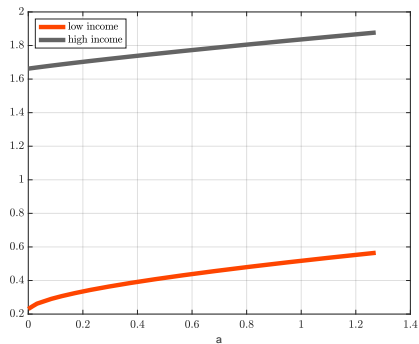
$$\begin{aligned}\mathbb{E} \left[V(a, \epsilon') \right] &= B(a, \epsilon) c_E = \sum_{\omega_i} \omega_i V(a, \rho\epsilon + \epsilon_i) = \sum_{\omega_i} \omega_i B(a, \rho\epsilon + \epsilon_i) c \\ &\rightarrow c_E = \underbrace{B(a, \epsilon)^{-1} \sum_{\omega_i} \omega_i B(a, \rho\epsilon + \epsilon_i) c}_{B^E}\end{aligned}$$

3. Guess c_0 and solve non-linear equation until convergence

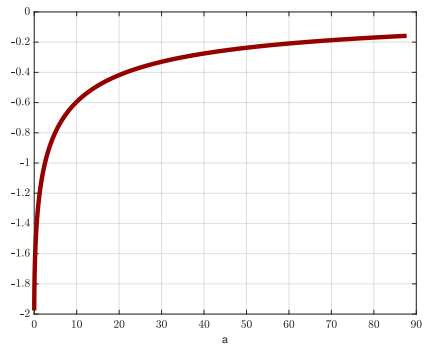
$$B(a, \epsilon) c_{j+1} = \max_{a' \geq 0} u \left(w\epsilon + (1+r)a - a' \right) + (a', \epsilon) B^E c_j$$

Consumption $c(a, \epsilon)$

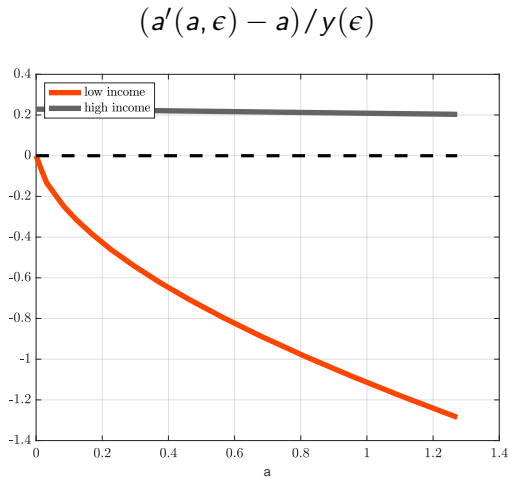
$$\tilde{c}(a, \epsilon)$$



$$\log \tilde{c}(a, \epsilon_L) - \log \tilde{c}(a, \epsilon_H)$$



Savings rate $(a'(a, \epsilon) - a)/y(\epsilon)$



Ergodic Distribution

- ▶ Aggregate assets are $A = \sum_{\epsilon} a \times \phi(a, \epsilon)$
- ▶ Assume $A = K$ in equilibrium then find r such that market clearing holds
- ▶ To aggregate we need to compute the Transition Probability Matrix (TPM) P using the policy functions
- ▶ Compute ergodic distribution $\phi(a, \epsilon)$ such that

$$\phi(a, \epsilon)P = \phi(a, \epsilon)$$

is a fixed point. We can solve it by computing the TPM and finding the eigenvector

Detour on Markov Processes

- ▶ A stochastic process is a sequence of random vectors. We typically use time to index it.
- ▶ A stochastic process has the *Markov property* if for all t and $k \geq 1$,

$$Prob(x_{t+1} | x_t, \dots, x_{t-k}) = Prob(x_{t+1} | x_t)$$

- ▶ Assuming the Markov Property we can characterize a process by a *Markov chain*.
 - ▶ π_0 initial distribution,
 - ▶ P transition matrix,

$$P_{ij} = Prob(x_{t+1} = e_j | x_t = e_i). \quad \sum_j P_{ij} = 1$$

- ▶ vector of zeros except 1 in entry i , e_i .

Detour on Markov Processes

- ▶ Probability of landing in state j in two periods

$$P_{ij}^{(2)} = \text{Prob}(x_{t+2} = e_j | x_t = e_i) = \sum_{h=1}^n \text{Prob}(x_{t+2} = e_j | x_{t+1} = e_h) \text{Prob}(x_{t+1} = e_h | x_t = e_i)$$

- ▶ Unconditional probabilities are therefore determined by

$$\pi'_1 = \text{Prob}(x_1) = \pi'_0 P$$

$$\pi'_2 = \text{Prob}(x_2) = \pi'_0 P^2$$

Detour on Markov Processes

- ▶ A stationary distribution satisfies

$$\pi' = \pi' P \quad \rightarrow \quad \pi'(I - P) = 0 \quad (I - P')\pi = 0$$

Does this distribution exist?

at least one unit eigenvalue & at least one eigenvector π normalized so that $\sum_i \pi_i = 1$.

- ▶ Multiplicity is possible.
- ▶ convergence? for given π_0

$$\lim_{t \rightarrow \infty} \pi_t = \pi_\infty$$

If yes and π_∞ independent of π_0 then the process is asymptotically stationary with unique distribution.

π_∞ is the asymptotic (or invariant) distribution of P .

Other Applications, for your future :)

- ▶ Compecon is very flexible and has very handy computational tools
- ▶ Discrete and continuous choice (e.g., problems with occupational choice and consumption-savings)
- ▶ Heterogeneous firms models

Panel Simulation

- ▶ We can also simulate many households
- ▶ For example: a standard simulated panel will follow this steps
 - ▶ select a very long period of time and N number of agents
 - ▶ make many draws of ϵ
 - ▶ use policy function to compute the consumption and assets of each agents
 - ▶ for initial conditions to remain irrelevant remove the first periods of the simulation
 - ▶ simulation can be "on the grid" or use a continuous process and interpolate the policy functions
- ▶ We can study micro behavior of consumption and income jointly, check if the distribution convergence to the one we compute inverting the TPM, etc

Aggregate Shocks

- ▶ Assume shock unexpected ("MIT" shock)
- ▶ Shock $\epsilon_0^Y < 0$ proportional shock with persistence $\rho^Y < 1$
- ▶ Computation
 - ▶ assume r fixed so no need to solve for prices along transition path
 - ▶ for t large enough we assume $Y_t = Y_\infty = Y$
 - ▶ steps: (i) policy functions along transition path backward iteration; (ii) simulate forward the distribution and compute aggregates
- ▶ Study cross-sectional responses to aggregate shock

Solving Transition Path

- ▶ Simplifications:

1. unexpected and perfect foresight about aggregate shock
2. r exogenous and endowment economy

- ▶ Backward computation of $\{c_t(a, \epsilon), a'_t(a, \epsilon)\}$

- ▶ at $t \geq T$ and $t < 0$ policy functions $\{c_t(a, \epsilon), a'_t(a, \epsilon)\} = \{c(a, \epsilon), a'(a, \epsilon)\}$
- ▶ for $t \in [0, T)$ we solve $\{c_t(a, \epsilon), a'_t(a, \epsilon)\}$ given $\{c_{t+1}(a, \epsilon), a'_{t+1}(a, \epsilon)\}$
 - ▶ same algorithm but without checking for convergence!
- ▶ using $\{c_t(a, \epsilon), a'_t(a, \epsilon)\}$ compute forward the $\{\phi_t(a, \epsilon)\}$ (and aggregates)
 - ▶ at T we may not be in the steady state distribution

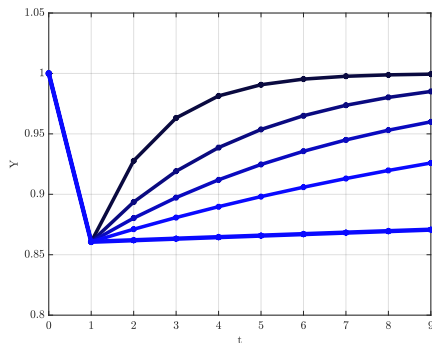
- ▶ Very simple to extend to a permanent shock where, e.g., $Y_\infty \neq Y$

Aggregate Shocks

► $\rho^Y = [0.5; 0.75; 0.85; .92; .99]$

► Assume $\nu = 0$

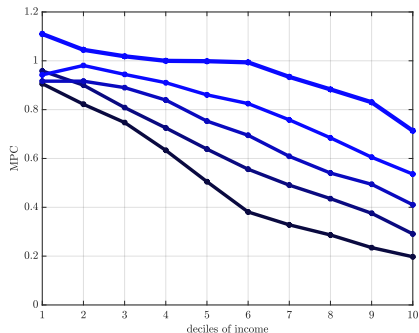
Y_t after Shock



Heterogeneous Responses

- ▶ Across deciles (repeated cross-section moment)
- ▶ Two moments: MPC $\frac{\bar{c}(Ye^{\epsilon_0^Y}, \epsilon_i) - \bar{c}(Y, \epsilon_i)}{Ye^{\epsilon_0^Y} - Y}$ and elasticity $\frac{\ln \bar{c}(Ye^{\epsilon_0^Y}, \epsilon_i) - \ln \bar{c}(Y, \epsilon_i)}{\epsilon_0^Y}$

MPC



Elasticity C-to-Y

