# Macroeconomics

Lecture 9: dynamic programming methods, part seven

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#### This class

- Practical stochastic dynamic programming
  - numerical integration to help compute expectations
  - using collocation to solve the stochastic optimal growth model

## Numerical integration (quadrature)

• Consider integral of a function f(x) against weights w(x)

$$\int f(x)w(x)\,dx$$

- Often not possible to calculate the integral exactly
- Can approximate the integral value by choosing an appropriate set of quadrature nodes  $x_i$  and weights  $w_i$  so that

$$\int f(x)w(x) dx \approx \sum_{i=1}^{n} f(x_i) w_i$$

• Various procedures for choosing nodes  $x_i$  and weights  $w_i$  (Newton-Cotes, Gaussian, Monte Carlo, etc)

## Gaussian quadrature

• Choose nodes  $x_i$  and weights  $w_i$  to satisfy 2n 'moment conditions'

$$\int x^k w(x) \, dx = \sum_{i=1}^n x_i^k w_i, \qquad k = 0, ...., 2n - 1$$

(2n nonlinear equations in 2n unknowns, nontrivial but standard routines exist)

- If x is a continuous random variable with PDF w(x) then Gaussian quadrature discretizes x, replacing it with n discrete points  $x_i$  and a PMF  $w_i$  on those discrete points
- The discretized version approximates the continuous version in the sense that the first 2n moments are the same

## Gaussian quadrature, 3-point example

- Suppose  $w(x) = \phi(x)$ , the standard normal density
- Choose 3 nodes and 3 weights to satisfy 6 moments

$$\mathbb{E}[x^0] = 1, \quad \mathbb{E}[x^1] = 0, \quad \mathbb{E}[x^2] = 1,$$
  
 $\mathbb{E}[x^3] = 0, \quad \mathbb{E}[x^4] = 3, \quad \mathbb{E}[x^5] = 0$ 

• Solution to system of 6 equations in 6 unknowns is

$$\begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \begin{pmatrix} -\sqrt{3} \\ 0 \\ +\sqrt{3} \end{pmatrix}, \qquad \begin{pmatrix} w_1 \\ w_2 \\ w_3 \end{pmatrix} = \begin{pmatrix} 1/6 \\ 2/3 \\ 1/6 \end{pmatrix}$$

## Normal example

• Using CompEcon tools

$$[x,w] = qnwnorm(n,mu,var)$$

• Then moments

$$\mathbb{E}[x] = \sum_{i=1}^{n} x_i w_i$$

$$\operatorname{Var}[x] = \sum_{i=1}^{n} x_i^2 w_i - \mathbb{E}[x]^2$$

## Lognormal example

• Similarly

## Using quadrature: AR1 example

• Suppose we want to compute

$$\mathbb{E}[f(z') \mid z]$$

for some function  $f(\cdot)$  that we can evaluate

• And suppose for given z that

$$z' = \rho z + \varepsilon, \qquad \varepsilon \sim \text{IID } N(\mu, \sigma^2)$$

## Using quadrature: AR1 example

• The exact integral is

$$\mathbb{E}[f(z') | z] = \int f(\rho z + \varepsilon) \phi(\varepsilon) d\varepsilon$$

(where again  $\phi(\cdot)$  denotes the standard normal density)

• We approximate this with the numerical integral

$$\mathbb{E}[f(z') | z] \approx \sum_{i=1}^{n} f(\rho z + \varepsilon_i) w_i$$

using the quadrature nodes and weights

## Quadrature and collocation

• Suppose we want to compute

$$\mathbb{E}[v(z') \mid z]$$

where  $v(\cdot)$  is approximated by basis functions

$$v(z') \approx \sum_{j=1}^{m} a_j \varphi_j(z')$$

• Then using quadrature

$$\mathbb{E}[v(z') | z] \approx \sum_{i=1}^{n} \sum_{j=1}^{m} a_j \varphi_j(\rho z + \varepsilon_i) w_i$$

## Quadrature and collocation

• To calculate this sum, we need to evaluate terms like

$$\varphi_j(\rho z + \varepsilon_i)$$

• Do this using the CompEcon tools, for example

```
zprime = rho*z+epsilon(i)
```

then

funeval(a,fspace,zprime)

## Stochastic growth example

• Let's solve the Bellman equation

$$v(k,z) = \max_{k'} \left\{ u(f(k,z) - k') + \beta \mathbb{E}[v(k',z') | z] \right\}$$

with the usual specification

$$f(k,z) = zk^{\alpha} + (1-\delta)k$$

$$u(c) = \frac{c^{1-\sigma} - 1}{1 - \sigma}$$

• And let's suppose that z' is an AR(1) in logs

$$\log z' = \rho_z \log z + \varepsilon, \qquad \varepsilon \sim \text{IID } N(0, \sigma_z^2)$$

## Stochastic growth example

Uses Matlab files in "stochastic\_growth\_example.zip" in LMS

## Productivity shocks

Inverting the uniform nodes gives a bit more control of the tails

## Capital stock

```
%%%%% grid for capital stock

nk = 99;  %% number of breakpoints for k grid
curv = 0.25;  %% (curv = 0 log-spaced, curv = 1 linear)

kmin = 1e-3;
kmax = (zmax/delta)^(1/(1-alpha));
kgrid = nodeunif(nk, kmin.^curv, kmax.^curv).^(1/curv);
```

### Function space for approximations

```
%%%% setup state space using CompEcon tools
fspace = fundef({'spli', kgrid},...
                  {'spli', zgrid}); % function space structure
grid
        = funnode(fspace); % nodes where we solve the problem
Phi
        = funbas(fspace); % matrix of collocation basis vectors
                          % Phi \{ij\} = phi j(k i)
kgrid
      = grid{1}; % extra 2 points for 3rd-order spline
zgrid
        = grid{2}; % extra 2 points for 3rd-order spline
kmin = kgrid(1);
kmax
        = kgrid(end);
zmin
        = zgrid(1);
        = zgrid(end);
zmax
```

#### Matrix with all combinations of states

#### Matrix with all combinations of states

• For example

$$S = gridmake([1;2;3],[4;5])$$

• Gives the matrix

$$S = \left[ egin{array}{cccc} 1 & 4 \ 2 & 4 \ 3 & 4 \ 1 & 5 \ 2 & 5 \ 3 & 5 \ \end{array} 
ight]$$

## Initial guess at collocation coefficients

```
%%%%% initial guess at collocation coefficients "a"

c = alpha*beta*z.*k.^alpha; % guess for consumption policy
v = log(c)/(1-beta); % guess for value function

a = Phi\v; % implied collocation coefficients
```

## Solve Bellman equation by collocation

```
%%%%% solve Bellman equation
for i=1:max_iter;
%%%%% optimal consumption given these coefficints
c = solve_brent('rhs_bellman',s,parameters,a,fspace,cmin,cmax,tol)
%%%% maximized rhs of Bellman equation
v = rhs_bellman(c,s,parameters,a,fspace); %% v(a)
```

Numerical routine solve\_brent does the maximization

## RHS of the Bellman equation

```
function y = rhs_bellman(c,s,parameters,a,fspace)

beta = parameters.beta;
sigma = parameters.sigma;

u = utility(c,sigma);

Ev = expected_value(c,s,parameters,a,fspace);

y = u+beta*Ev;
```

# Evaluating $\mathbb{E}[v(k',z')|z]$

```
function y = expected_value(c,s,parameters,a,fspace)
```

```
Ev = 0;
kprime = z.*(k.^alpha) + (1-delta)*k-c;
for j=1:numel(ez),
zprime = max(min(z.^rhoz.*exp(ez(j)), zmax), zmin);
sprime = [kprime, zprime];
Ev = Ev+wz(j)*funeval(a,fspace,sprime);
end
y = Ev;
```

# Evaluating $\mathbb{E}[v(k',z')|z]$

• This last step computes

$$\mathbb{E}[v(k',z')\,|\,z]$$

where  $v(\cdot)$  is approximated by basis functions

$$v(k',z') \approx \sum_{i=1}^{n_s} a_i \phi_i(k',z')$$

• Using quadrature to compute the expectation

$$\mathbb{E}[v(k',z') | z] \approx \sum_{j=1}^{n_z} \sum_{i=1}^{n_s} a_i \, \phi_i (zk^{\alpha} + (1-\delta)k - c, z^{\rho_z} e^{\varepsilon_j}) \, w_j$$

## Updating coefficients

```
Jacobian = 0;
%%%%% implied by optimal consumption
kprime = z.*(k.^alpha) + (1-delta)*k-c;
%%%%% build up Jacobian matrix of v(a)
for j=1:numel(ez),
zprime = max(min(z.^rhoz.*exp(ez(j)), zmax), zmin);
sprime = [kprime, zprime];
Jacobian = Jacobian+beta*wz(j)*funbas(fspace, sprime);
end
%%%% Newton's method
anew = a - (Phi-Jacobian) \ (Phi * a - v);
```

## Check if converged

```
%%%%% check if converged
error = norm(anew-a,inf);
fprintf('%4i %6.2e \n',[i, error]);
if error<tol, break, end;</pre>
%%%%% if not converged, update and try again
a = anew;
end
```

## Reshape solution

```
%%%%% reshape solution

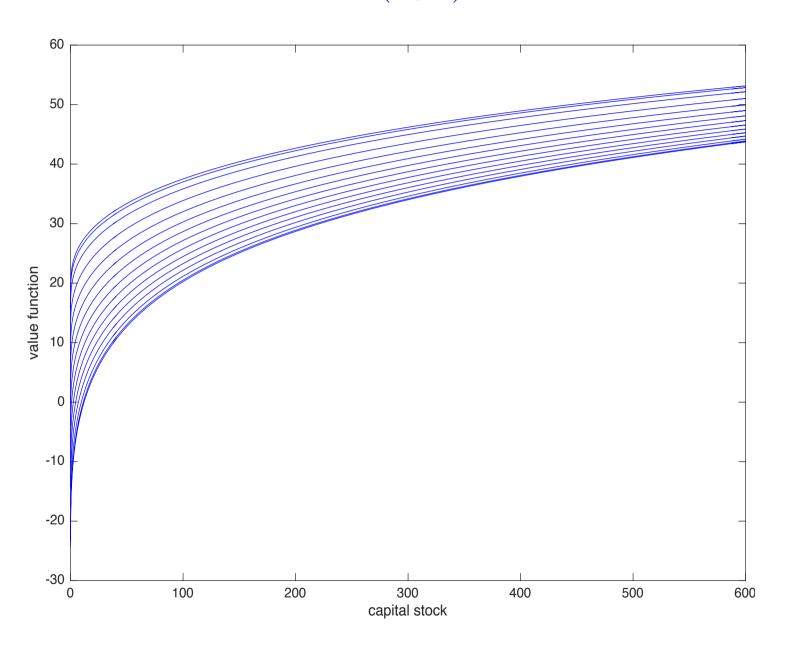
Nk = numel(kgrid);
Nz = numel(zgrid);

VV = reshape(v,Nk,Nz); %% VV = v(k_i,z_j)
CC = reshape(c,Nk,Nz); %% CC = c(k_i,z_j)

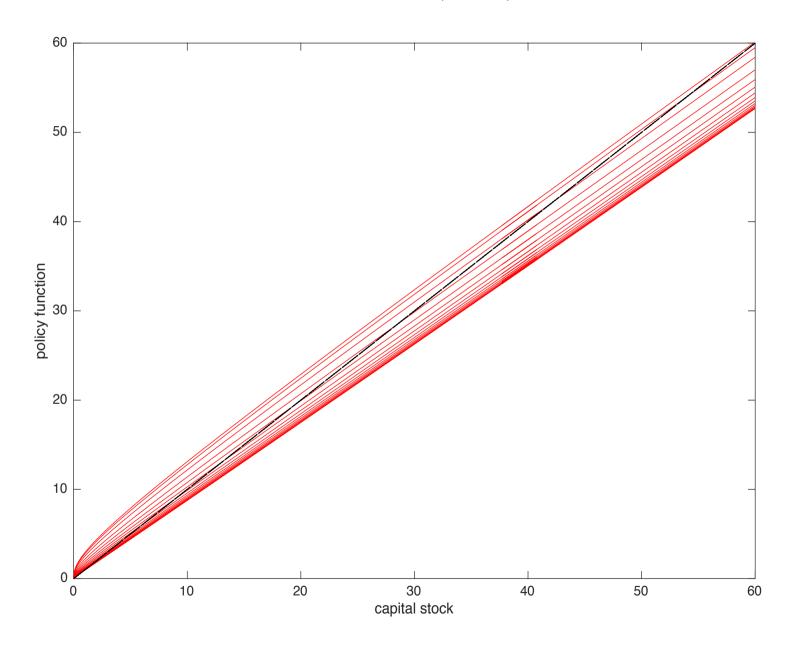
%%%% optimal policy k'=g(k,z)
GG = reshape(kprime,Nk,Nz); %% GG = g(k_i,z_j)
```

As usual with collocation methods, can also now interpolate as needed

# Value function v(k, z) for various z



# Policy function k' = g(k, z) for various z



### Next class

• Dynamic programming applications