

Advanced Macro I

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Lecture 13: Dynamic programming in continuous time

Outline

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- ▶ Today we start using our tools for dynamic programming.
 - ▶ no uncertainty
 - ▶ Markov chains
- ▶ We review some simple applications.

From last time

Solutions to the teamwork assignments

- ▶ Both CEU email servers had the following stationary distribution:

$$\pi_n^* = 1/N$$

for $n = 0, 1, \dots, N - 1$ and 0 thereafter.

- ▶ It was easiest to see for server 2, because the Kolmogorov equation gave $\pi_n^* = \pi_{n-1}^*$ and $\pi_0^* = \pi_{N-1}^*$.

Solutions to the teamwork assignments

- For server 1,

$$\lambda\pi_{N-1}^* = (\lambda + \eta)\pi_N^*$$

so the stationary distribution is

$$\pi_n^* = \begin{cases} \frac{\lambda + \eta}{N(\lambda + \eta) + \lambda} & \text{if } n < N \\ \frac{\lambda}{N(\lambda + \eta) + \lambda} & \text{if } n = N \end{cases}$$

- Take $\eta \rightarrow \infty$ to get the result.

Discrete time

Dynamic programming with no uncertainty

- ▶ Suppose you have a vector of state variables x_t , and control variables c_t .
- ▶ The equation of motion for the state is

$$\Delta x_{t+1} = F(x_t, c_t).$$

- ▶ Per-period utility is

$$u(x_t, c_t)$$

- ▶ The sequential problem is

$$\max_{\{c_t\}} \sum_{t=1}^{\infty} \beta^t u(x_t, c_t) \text{ s.t. } \Delta x_{t+1} = x_t + F(x_t, c_t)$$

The recursive formulation

- ▶ The corresponding Bellman equation is

$$V(x_t) = \max_{c_t} \{u(x_t, c_t) + \beta V(x_{t+1})\}$$

- ▶ or substituting in the equation of motion

$$V(x_t) = \max_{c_t} \{u(x_t, c_t) + \beta V[x_t + F(x_t, c_t)]\}$$

Solution

- ▶ The solution is a value function $V(x)$ that maps the state into the PDV of utility.
- ▶ Equivalently, the solution can be given as a policy function $c(x)$.
- ▶ What would change if time periods were days instead of years?

Continuous time

Moving to continuous time

- ▶ Let time periods be Δ apart.
- ▶ As before, we want to characterize the time series as Δ becomes smaller and smaller.
- ▶ We take the limit as $\Delta \rightarrow 0$.
 - ▶ We will have to rescale flows, but not stocks.

Differential equations

- Now dynamics are characterized by the differential equation:

$$\dot{x}(t) = \lim_{\Delta t \rightarrow 0} \frac{F(x_t, c_t, \Delta t)}{\Delta t} \equiv f(x_t, c_t).$$

Dynamic programming

- ▶ Back to our discrete-time Bellman:

$$V(x_t) = \max_{c_t} \{u(x_t, c_t) + \beta V[x_t + F(x_t, c_t)]\}$$

- ▶ Which of the objects here depend on the length of the time period?

Dynamic programming

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$$V(x_t) = \max_{c_t} \{u(x_t, c_t) + \beta V[x_t + F(x_t, c_t)]\}$$

- ▶ Which of the objects here depend on the length of the time period?
 - ▶ u , because utility is a *flow*: shorter time periods yield less utility
 - ▶ β , because shorter time periods are discounted less
 - ▶ F as we have seen above

Dynamic programming

- ▶ Back to our discrete-time Bellman:

$$V(x_t) = \max_{c_t} \{u(x_t, c_t) + \beta V[x_t + F(x_t, c_t)]\}$$

- ▶ Which of the objects here depend on the length of the time period?
 - ▶ u , because utility is a *flow*: shorter time periods yield less utility
 - ▶ β , because shorter time periods are discounted less
 - ▶ F as we have seen above
- ▶ Let us make this period dependence explicit:

$$V(x_t) = \max_{c_t} \left\{ u(x_t, c_t)\Delta + \frac{1}{1 + \rho\Delta} V[x_t + f(x_t, c_t)\Delta] \right\}$$

- ▶ Now u is the *per-period* utility, ρ is the *per-period* discount rate, f is the *per-period* growth rate.

Infinitesimal periods

As you might expect, we take Δ to 0.

First multiply by $(1 + \rho\Delta)$:

$$(1 + \rho\Delta)V(x_t) = \max_{c_t} \{u(x_t, c_t)\Delta(1 + \rho\Delta) + V[x_t + f(x_t, c_t)\Delta]\}$$

Then subtract $V(x_t)$:

$$\rho\Delta V(x_t) = \max_{c_t} \{u(x_t, c_t)\Delta(1 + \rho\Delta) + V[x_t + f(x_t, c_t)\Delta] - V(x_t)\}$$

Then divide by Δ :

$$\rho V(x_t) = \max_{c_t} \left\{ u(x_t, c_t)(1 + \rho\Delta) + \frac{V[x_t + f(x_t, c_t)\Delta] - V(x_t)}{\Delta} \right\}$$

Now we're ready to take the limit.

The Hamilton-Jacobi-Bellman equation

$$\rho V(x_t) = \max_{c_t} [u(x_t, c_t) + V'(x_t)f(x_t, c_t)]$$

$$= \frac{\partial V}{\partial t} = \frac{\partial V}{\partial x} \frac{\partial x}{\partial t}$$

► What is different:

- we have ρV , not V on the LHS
- we have \dot{V} , not new value on RHS

$$\langle \nabla V, \dot{x} \rangle$$

► Intuition:

- the per-period discount loss from my value should be compensated by
- flow utility
- and (expected) gains in future value

Teamwork: eat-the-pie problem

- ▶ You have wealth W , accruing interest r per unit of time.
- ▶ You maximize

$$\int_{t=0}^{\infty} \exp(-\rho t) \ln c(t) dt.$$

1. Write down the Bellman equation.
2. Guess that $V(W) = a + b \ln W$ and solve for a and b .
3. What is the optimal consumption policy, $c(W)$?

Application to the Ramsey model

► Let

$$\begin{aligned}x_t &= k_t, \\u(x_t, c_t) &= c_t^{1-\theta} / (1 - \theta), \\f(x_t, c_t) &= f(k_t) - \delta k_t - c_t\end{aligned}$$

► The Bellman equation is now

$$\rho V(k) = \max_c \left\{ \frac{c^{1-\theta}}{1-\theta} + V'(k)[f(k) - \delta k - c] \right\}$$

Deriving the Euler equation

- ▶ The FOC for optimal c :

$$c^{-\theta} = V'(k).$$

- ▶ Taking logs and differentiating wrt time

$$-\theta \hat{c} = \frac{V''(k)}{V'(k)} [f(k) - \delta k - c]$$

(\hat{x} denotes \dot{x}/x)

- ▶ Differentiating through the Bellman to express $V'(k)$:

$$\rho V'(k) = V''(k)[f(k) - \delta k - c] + V'(k)[f'(k) - \delta]$$

- ▶ Substituting in $V''(k)$:

$$\hat{c} = \frac{1}{\theta} [f'(k) - \delta - \rho] \equiv \frac{1}{\theta} [r(k) - \rho]$$

The consumption rule

$$\hat{c} = \frac{1}{\theta}[f'(k) - \delta - \rho] \equiv \frac{1}{\theta}[r(k) - \rho]$$

- ▶ Agents like to smooth consumption (especially with high θ).
- ▶ Consumption grows if $r > \rho$: the market return on my saving (late consumption) is higher than the private return from early consumption.
- ▶ Consumption growth is high if k is low (r is high).

Uncertainty

Moments of a Markov chain

- ▶ Take a function $v()$ that assigns each state a value, v_1, \dots, v_N .
- ▶ What is the expected value of v in a short period of time if we are in state s_i now?
- ▶ If $\Delta \approx 0$, the probability of moving from the state is ≈ 0 , so the expected value is $\approx v_i$.
- ▶ It is more meaningful to talk about the "rate" of change, as in the case of differential equations.
- ▶ What is the *expected rate of change* in v ?

$$\frac{E(dv)}{dt} = \lim_{\Delta \rightarrow 0} \frac{E(v_{t+\Delta}|t) - v_t}{\Delta}$$

Expectations

- ▶ Again, start from discrete time:

$$E[v(t + \Delta)|t] = (1 - \sum_{j \neq i} \Delta \lambda_{ij})v_i + \sum_{j \neq i} \Delta \lambda_{ij}v_j$$

- ▶ Subtract $v_i = v(t)$ from both sides and divide by Δ :

$$\frac{E[v(t + \Delta)|t] - v(t)}{\Delta} = \sum_{j \neq i} \lambda_{ij}(v_j - v_i)$$

- ▶ Taking $\Delta \rightarrow 0$ $E(dv) = \sum \Delta \lambda_{ij} (v_j - v_i)$

$$E\left(\frac{dv}{dt}\right) = \frac{E(dv)}{dt} = \sum_{j \neq i} \lambda_{ij}(v_j - v_i)$$

- ▶ Intuitively, the expected change is a weighted average of all potential changes.
- ▶ A change of $v_j - v_i$ arrives with arrival rate λ_{ij} , so has a weight λ_{ij} .

Dynamic programming

- ▶ We can derive the continuous-time HJB equation with uncertainty as

$$\rho V(x_i) = \max_c \left[u(x_i, c) + \frac{E dV(x)}{dt} \right]$$

- ▶ The only change is that we have *expected* change in V on the RHS.
 1. This holds if x is a jump process.
 2. x is continuous
 3. x is a mix of the two

Dynamic programming

- ▶ Suppose our state x follows a Markov chain as above.
- ▶ Arrival rates λ_{ij} may depend on past states (i) and on the policy variable c .
- ▶ Because x is a jump process,

$$\frac{EdV(x)}{dt} = \sum_{j \neq i} \lambda_{ij} [V(x_j) - V(x_i)].$$

- ▶ The HJB equation simplifies to

$$\rho V(x_i) = \max_c \left\{ u(x_i, c) + \sum_{j \neq i} \lambda_j(x_i, c) [V(x_j) - V(x_i)] \right\}$$

Dynamic programming

- ▶ More generally, suppose x follows a Markov chain, and y is a continuous state variable.
- ▶ The HJB equation can be written as

$$\rho V(x_i, y) = \max_c \left\{ u(x_i, y, c) + \sum_{j \neq i} \lambda_j(x_i, y, c) [V(x_j, y) - V(x_i, y)] + f(x_i, y, c) V_y(x_i, y) \right\}$$

Dynamic programming

- ▶ More generally, suppose x follows a Markov chain, and y is a continuous state variable.
- ▶ The HJB equation can be written as

$$\rho V(x_i, y) = \max_c \left\{ u(x_i, y, c) + \sum_{j \neq i} \lambda_j(x_i, y, c) [V(x_j, y) - V(x_i, y)] \right\} + f(x_i, y, c) V_y(x_i, y)$$

$$V(x, y_{t+\Delta}) - V(x, y_t) \approx V_y \Delta$$

- ▶ This only applies if y does not change when x jumps.
 - ▶ y is an aggregate variable, x is individual

- ▶ Otherwise the jump would have to be accounted for.

- ▶ The reverse does not matter. Why?

$$E[V(x', y_{t+\Delta}) - V(x, y_t)] \approx V_y \Delta \wedge \Delta = O(\Delta^2) = o(\Delta)$$

Checklist

By now you should understand

1. forward Kolmogorov equation
2. stationary distribution
3. Poisson process
4. Poisson distribution
5. moments of a Markov chain
6. Hamilton–Jacobi–Bellman equation with
 - ▶ continuous deterministic states
 - ▶ jump processes

Applications

Applications

- ▶ We consider three simple applications
 1. A model of exogenous job loss and job finding.
 2. A model of endogenous job search.
 3. A model of a milk farm.

Exogenous job search

Exogenous job search

- ▶ There are only two states:
 - ▶ E_1 : worker has a job
 - ▶ E_2 : worker is unemployed
- ▶ Transition across states (job loss, job finding) is exogenous (for now).
 - ▶ No optimization involved.
 - ▶ This is just a simple way of calculating the NPV of a job.

Exogenous job search

- ▶ The hazard rate of losing a job is δ .
- ▶ The arrival rate of a new job for an unemployed is λ .

Exogenous job search

- ▶ The per-period value of holding a job is w .
- ▶ The per-period value of being unemployed is b .
- ▶ What is the overall (present discounted) value of a job?

$$V_J = \int_{t=0}^{\infty} \exp(-\rho t) u(S_t).$$

- ▶ S_t is random and varies over time.
- ▶ We may have to evaluate a complex integral.
- ▶ Dynamic programming makes our lives easier.

The Bellman equation

- ▶ The Bellman equation characterizing the value of a job

$$\rho V_J = w + \delta(V_U - V_J).$$

- ▶ The Bellman equation characterizing the value of unemployment

$$\rho V_U = b + \lambda(V_J - V_U).$$

- ▶ Note that you can think of the value function as $V(s)$ with s taking only two values.
- ▶ This looks much simpler! A system of two linear equations with two unknowns.

Solution

- ▶ The solution is

$$\begin{aligned} \rho V_J &= \frac{1}{\rho} \left[\frac{\rho + \lambda}{\rho + \lambda + \delta} w + \frac{\delta}{\rho + \lambda + \delta} b \right] \\ \rho V_U &= \frac{1}{\rho} \left[\frac{\rho + \delta}{\rho + \lambda + \delta} b + \frac{\lambda}{\rho + \lambda + \delta} w \right] \end{aligned}$$

- ▶ The value of a job is the weighted average of the PDV of wages and the PDV of benefits.
- ▶ The weights depend on all parameters.

Comparative statics

- ▶ The value of a job is increasing in
 - ▶ wages
 - ▶ benefits
 - ▶ job finding rate
- ▶ Decreasing in
 - ▶ discount rate
 - ▶ firing rate
- ▶ Converges to the PDV of wages w/ρ as
 - ▶ δ goes to zero
 - ▶ λ goes to infinity

Endogenous job search

Endogenous job search

- ▶ We now endogenize job search. Everything else remains the same.
- ▶ To make sure that jobs arrive at rate λ , the unemployed has to pay a search cost $g(\lambda)$.
 - ▶ g is increasing, convex, twice differentiable, lnada
- ▶ Note that $g(\lambda)$ is a flow: the search effort at a given moment in time.
- ▶ λ is also a flow: the probability of success at a given moment in time.
- ▶ This still a memoryless process:
 - ▶ past search efforts have no effect
 - ▶ (just as time has no effect)



The Bellman equation

- ▶ The Bellman is now

$$\begin{aligned}\rho V_J &= w + \delta(V_U - V_J) \\ \rho V_U &= \max_{\lambda} [b - g(\lambda) + \lambda(V_J - V_U)]\end{aligned}$$

- ▶ Note the maximization in the unemployed state.

First-order condition

- ▶ The FOC for λ is

$$g'(\lambda^*) = V_J - V_U$$

- ▶ The "exogenous" Bellman still correctly calculates V_J and V_U once we substitute in the new benefits $b - g(\lambda^*)$ and the job finding rate λ^* .
- ▶ Find a λ^* that satisfies both the FOC and the Bellman.

Solution

- ▶ Subtracting the two Bellman equations:

$$V_J - V_U = \frac{w - b + g(\lambda^*)}{\rho + \delta + \lambda^*}$$

- ▶ Substitute this into FOC to get an implicit solution for λ^* :

$$g'(\lambda^*) = \frac{w - b + g(\lambda^*)}{\rho + \delta + \lambda^*}$$

$$(\rho + \delta + \lambda^*) g'(\lambda^*) = w - b + g(\lambda^*)$$



Comparative statics

- ▶ Totally differentiating the implicit function...
- ▶ search intensity λ^* is
 - ▶ increasing in $w - b$
 - ▶ decreasing in $\rho + \delta$
 - ▶ decreasing with an upward shift of search costs

A milk farm

- ▶ Our last application considers a milk farm with n cows.
- ▶ The only state variable is n .
- ▶ The control variable is the feed c we give to each cow.

Flow profits

- ▶ Each cow gives $m(c)$ milk per period of time.
 - ▶ m is increasing and concave.
- ▶ Flow profits are

$$\pi = [pm(c) - wc]n,$$

where

- ▶ p is the price of milk
- ▶ w is the price of feed

Dynamics

- ▶ New cows are born at rate λ to each existing cow (not modeled).
- ▶ Cows die at rate $\delta(c)$.
 - ▶ δ is decreasing and convex
- ▶ What is the dynamics of n ?
- ▶ Over a Δ period of time, n becomes
 - ▶ $n + 1$ with probability $\lambda n \Delta$
 - ▶ $n - 1$ with probability $\delta(c)n \Delta$
 - ▶ n with probability $1 - [\lambda + \delta(c)]\Delta$

Valuing the farm

- ▶ What is the value of the farm?
- ▶ The Bellman equation

$$\begin{aligned}\rho V(n) = \max_c \{ & [pm(c) - wc]n + \\ & \lambda n[V(n+1) - V(n)] + \\ & \delta(c)n[V(n-1) - V(n)] \}\end{aligned}$$

Solution

- ▶ Guess that $V(n) = vn$.

$$\rho vn = \max_c \{ [pm(c) - wc]n + \lambda n[v] + \delta(c)n[-v] \}$$

or

$$\rho v = \max_c \{ pm(c) - wc + [\lambda - \delta(c)]v \}$$

- ▶ FOC for c

$$pm'(c) - w - v\delta'(c) = 0$$

- ▶ Find c and v so that both are satisfied.

Appendix

Empty slides for notes

$$\dot{W} = rW - c + y$$

$$W_{t+\Delta} = W_t + r\Delta W_t - C_t\Delta + y_t\Delta$$

$$\frac{W_{t+\Delta} - W_t}{\Delta} = rW_t - C_t + y_t$$

\downarrow

$$\dot{W}_t$$

Empty slides for notes

$$g V(W_t) = \max_c \left\{ \ln(c_t) + V'(W_t) (r W_t - c_t) \right\}$$

$$\frac{1}{c_t} = V'(W_t) = \frac{r}{W_t} \quad c_t = \frac{1}{r} W_t$$

$$g a + g r \ln W = -\ln r + \ln W_t \quad (1)$$

$$+ \frac{r}{W_t} (r W_t - \frac{1}{r} W_t) \quad \frac{1}{r} = g$$

Empty slides for notes

$$a = \frac{1}{\bar{g}} \left(\frac{v}{g} + \ln g - 1 \right)$$

Empty slides for notes