#### Advanced Tools in Macroeconomics

Continuous time models (and methods)

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#### Introduction

- In this lecture we will look at the Ramsey growth model
- We will show how to derive it's continuous time formulation, known as the Hamilton-Jacobi-Bellman equation
- And introduce a method on how to solve it (known as the "explicit method")

Now consider the Ramsey growth model (without growth)

$$v(k_t) = \max_{c_t, k_{t+1}} \{ u(c_t) + (1 - \rho)v(k_{t+1}) \}$$
  
s.t.  $c_t + k_{t+1} = k_t^{\alpha} + (1 - \delta)k_t$ 

 $\triangleright$  In  $\triangle$  units of time

$$v(k_t) = \max_{c_t, k_{t+\Delta}} \{ \Delta u(c_t) + (1 - \Delta \rho) v(k_{t+\Delta}) \}$$
s.t.  $\Delta c_t + k_{t+\Delta} = \Delta k_t^{\alpha} + (1 - \Delta \delta) k_t$ 

- ▶ Notice that all flows change when the length of the time period on which they are defined changes. Stocks, *k*, are the same.
- ▶ I discount the future with  $1 \Delta \rho$  instead of  $(1 \rho)$  (or with  $e^{-\Delta \rho}$  instead of  $e^{\rho}$ , but these are, in the limit, equivalent).
- ▶ One funny thing: Consumption, c, is still "monthly" consumption, but it now only cost  $\Delta$  as much, and I only get a  $\Delta$  fraction of the utility!
- ► These assumptions are for technical reasons, and it will (hopefully) soon be clear why they are made.

Bellman equation

$$v(k_t) = \max_{c_t, k_{t+\Delta}} \{ \Delta u(c_t) + (1 - \Delta \rho) v(k_{t+\Delta}) \}$$
  
s.t.  $\Delta c_t + k_{t+\Delta} = \Delta k_t^{\alpha} + (1 - \Delta \delta) k_t$ 

Subtract  $v(k_t)$  from both sides and insert the budget constraint into  $v(k_{t+\Delta})$ 

$$0 = \max_{c_t} \{ \Delta u(c_t) + v(k_t + \Delta(k_t^{\alpha} - \delta k_t - c_t)) - v(k_t) - \Delta \rho v(k_t + \Delta(k_t^{\alpha} - \delta k_t - c_t)) \}$$

From before

$$0 = \max_{c_t} \{ \Delta u(c_t) + v(k_t + \Delta(k_t^{\alpha} - \delta k_t - c_t)) - v(k_t) - \Delta \rho v(k_t + \Delta(k_t^{\alpha} - \delta k_t - c_t)) \}$$

Divide by Δ

$$0 = \max_{c_t} \{ u(c_t) + \frac{v(k_t + \Delta(k_t^{\alpha} - \delta k_t - c_t)) - v(k_t)}{\Delta} - \rho v(k_t + \Delta(k_t^{\alpha} - \delta k_t - c_t)) \}$$

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ightharpoonup Take limit  $\Delta o 0$  and rearrange

$$\rho v(k_t) = \max_{c_t} \{ u(c_t) + v'(k_t)(k_t^{\alpha} - \delta k_t - c_t) \}$$

► This is know as the Hamilton-Jacobi-Bellman (HJB) equation.

Dropping time notation we have

$$\rho v(k) = \max_{c} \{ u(c) + v'(k)(k^{\alpha} - \delta k - c) \}$$

▶ This is simple to solve and (can be) blazing fast!

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- This is simple to solve and (can be) blazing fast!
- Why fast? Maximization is trivial: First order condition

$$u'(c) = v'(k)$$

So if we know v'(k) we know optimal c without searching for it!

- ▶ How do we find v'(k)?
- Suppose we have hypothetical values of v(k) on a uniformly spaced grid of k,  $\mathcal{K} = \{k_0, k_1, \dots, k_N\}$  with stepsize  $\Delta k$ .
- We can then approximate v'(k) at gridpoint  $k_i$   $(i \neq 1, N)$  as

$$v'(k_i) = 0.5(v(k_{i+1}) - v(k_i))/\Delta k + 0.5(v(k_i) - v(k_{i-1}))/\Delta k$$

or

$$v'(k_i) = \frac{v(k_{i+1}) - v(k_{i-1})}{2\Delta k}$$

ightharpoonup and for  $k_1$  and  $k_N$ 

$$v'(k_1) = (v(k_2) - v(k_1))/\Delta k$$

and

$$v'(k_N) = (v(k_N) - v(k_{N-1}))/\Delta k$$

▶ There are many ways of doing this. If you have a vector of v(k) values – call it V – then dV=gradient(V)/dk.

- I prefer an alternative method.
- Construct the matrix D as

$$D = \begin{pmatrix} -1/dk & 1/dk & 0 & 0 & \dots & 0 \\ -0.5/dk & 0 & 0.5/dk & 0 & \dots & 0 \\ 0 & -0.5/dk & 0 & 0.5/dk & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & 0 & -1/dk & 1/dk \end{pmatrix}$$

► Then

$$v'(k) \approx D \times v(k)$$

#### Algorithm

- 1. Construct a grid for k.
- 2. For each point on the grid, guess for a value of  $V_0$ .
- 3. Calculate the derivative as  $dV_0=D*V_0$ .
- 4. Find V<sub>1</sub> from

$$\rho V_1 = u(c_0) + dV_0(k^{\alpha} - \delta k - c_0),$$
with  $u'(c_0) = dV_0$ 

5. Back to step 3 with  $V_1$  replacing  $V_0$ . Repeat until convergence.

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Beware: The contraction mapping theorem does not work, so convergence is an issue. Solution: update slowly. That is,  $V_1 = \gamma V_1 + (1 - \gamma) V_0$ , for a low value of  $\gamma$ .



#### Alternative algorithm

- 1. Construct a grid for k.
- 2. For each point on the grid, guess for a value of  $V_0$ .
- 3. Calculate the derivative as  $dV_0=D*V_0$ .
- 4. Find V<sub>1</sub> from

$$V_1 = \Gamma(u(c_0) + dV_0(k^{\alpha} - \delta k - c_0) - \rho V_0) + V_0,$$
  
with  $u'(c_0) = dV_0$ 

5. Back to step 3 with  $V_1$  replacing  $V_0$ . Repeat until convergence.

We will take a look at an alternative way of doing things tomorrow.

#### Alternative vs. standard algorithm

- But to me they sort of look the same
- ► I.e.

$$egin{aligned} V_1 &= \gamma rac{1}{
ho} (u(c_0) + dV_0 (k^lpha - \delta k - c_0)) + (1 - \gamma) V_0 \ &= rac{\gamma}{
ho} (u(c_0) + dV_0 (k^lpha - \delta k - c_0) - 
ho V_0) + V_0 \end{aligned}$$

▶ So as long as  $\frac{\gamma}{\rho} = \Gamma$  they should be identical.