Advanced Tools in Macroeconomics

Continuous time models (and methods)

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Plan for these slides

- 1. Speeding things up while making them more robust
 - 1.1 Use the "implicit method" to somewhat bring back the contraction property
 - 1.2 Make use of sparsity

▶ The Ramsey growth model in continuous time is

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

The explicit method suggests

$$\rho v_{n+1}(k) = \max_{c} \{ u(c) + v'_n(k)(f(k) - \delta k - c) \}.$$

▶ But this breaks down without a (very small) smoothing parameter



Why? Consider the deterministic Ramsey growth model in discrete time

$$v(k) = \max_{c} \{ u(c) + (1 - \rho)v(f(k) + (1 - \delta)k - c) \}.$$

In discrete time we iterate as

$$v_{n+1}(k) = \max_{c} \{u(c) + (1-\rho)v_n(f(k) + (1-\delta)k - c)\},\$$

▶ This is a contraction mapping and we know that $v_n \rightarrow v$.

Let's, heuristically, convert this into continuous time

$$v_{n+1}(k) = \max_{c} \{\Delta u(c) + (1 - \Delta \rho)v_n(k + \Delta (f(k) - \delta k - c))\}.$$

$$0 = \max_{c} \{u(c) + \frac{v_n(k + \Delta(f(k) - \delta k - c)) - v_{n+1}(k)}{\Delta} - \rho v_n(k + \Delta(f(k) - \delta k - c))\}.$$

Taking limits and rearranging

$$\rho v_n(k) = \max_{c} \{u(c) + \lim_{\Delta \to 0} \frac{v_n(k + \Delta(f(k) - \delta k - c)) - v_{n+1}(k)}{\Delta}\}.$$

Problem 1:

$$\lim_{\Delta \to 0} \frac{v_n(k + \Delta(f(k) - \delta k - c)) - v_{n+1}(k)}{\Delta} \\ \neq v_n'(k)(f(k) - \delta - c)$$

The right hand side of the HJB equation contains v_{n+1} .

Problem 2: The left hand side of the HJB equation is v_n .

Take a look at the previous equation

$$\rho v_n(k) = \max_{c} \{u(c) + \lim_{\Delta \to 0} \frac{v_n(k + \Delta(f(k) - \delta k - c)) - v_{n+1}(k)}{\Delta}\}.$$

▶ Subtract $v_n(k)/\Delta$ from both sides and rearrange

$$\lim_{\Delta \to 0} \frac{v_{n+1}(k) - v_n(k)}{\Delta} = \max_{c} \{u(c) + \lim_{\Delta \to 0} \frac{v_n(k + \Delta(f(k) - \delta k - c)) - v_n(k)}{\Delta} - \rho v_n(k)\}.$$

$$\lim_{\Delta \to 0} \frac{v_{n+1}(k) - v_n(k)}{\Delta} = \max_{c} \{u(c) + \lim_{\Delta \to 0} \frac{v_n(k + \Delta(f(k) - \delta k - c)) - v_n(k)}{\Delta} - \rho v_n(k)\}.$$

► Which is approximately

$$v_{n+1}(k) = v_n(k) + \Gamma \times \max_{c} \{u(c) + v'_n(k)(f(k) - \delta k - c) - \rho v_n(k)\}.$$

if Γ is sufficiently small!

$$v_{n+1}(k) = v_n(k) + \Gamma \times \max_{c} \{u(c) + v'_n(k)(f(k) - \delta k - c) - \rho v_n(k)\}.$$

- This is just a reformulation of the explicit method.
- ▶ But it gives and indication why it can converge if the smoothing parameter is close to zero.
- ▶ In any case, there is a better better method available, and we will go through it next.

Back to discrete time

$$v_{n+1}(k) = \max_{c} \{u(c) + (1-\rho)v_n(f(k) + (1-\delta)k - c)\},\$$

- ► Call the optimal choice c_n (it's really a function of k but I'm saving some space)
- Howard's Improvement Algorithm says that we can then iterate on

$$v_{n+1}^{h+1}(k) = u(c_n) + (1-\rho)v_{n+1}^h(f(k) + (1-\delta)k - c_n)\},$$

with $v_{n+1}^0 = v_n$.

▶ Until $v_{n+1}^{h+1} \approx v_{n+1}^h$. This can speed things up considerably, and preserves the contraction property



Suppose that it holds exactly $v_{n+1}^{h+1} = v_{n+1}^h$, and let's just call this function v_{n+1} . Then it must satisfy

$$v_{n+1}(k) = u(c_n) + (1-\rho)v_{n+1}(f(k) + (1-\delta)k - c_n),$$

ightharpoonup In Δ units of time

$$v_{n+1}(k) = \Delta u(c_n) + (1 - \Delta \rho)v_{n+1}(k + \Delta (f(k) - \delta k - c_n)).$$

Rearrange

$$0 = u(c_n) + \frac{v_{n+1}(k + \Delta(f(k) - \delta k - c_n)) - v_{n+1}(k)}{\Delta} - \rho v_{n+1}(k + \Delta(f(k) - \delta k - c_n))\}.$$

and take limits

$$\rho v_{n+1}(k) = u(c_n) + v'_{n+1}(k)(f(k) - \delta k - c_n),$$

$$\rho v_{n+1}(k) = u(c_n) + v'_{n+1}(k)(f(k) - \delta k - c_n),$$

- Now the awkward discrepancy between v_{n+1} and v_n is gone!
- But the problem looks a bit hard to solve!
- ► Turns out it is not!
- ► This is where the "implicit method" comes in.

- 1. Start with a grid for capital $\mathbf{k} = [k_1, k_2, \dots, k_N]$.
- 2. For each grid point for capital you have a guess for $v_0(k_i)$, $\forall k_i \in \mathbf{k}$
- 3. So you have a vector of N values of v_0 . Call this \mathbf{v}_0
- 4. You should also have a difference operator (an $N \times N$ matrix) **D** such that

$$\mathbf{Dv} \approx \mathbf{v}'(k), \quad \forall k_i \in \mathbf{K}$$



5. Optimal consumption choice given by FOC

$$u'(\mathbf{c}_0) = \mathbf{D}\mathbf{v}_0$$

reasonable to call this $c(\mathbf{v}_0)$ – an $N \times 1$ vector

6. This implies another $N \times 1$ vector of savings

$$\mathbf{s}_0 = (f(\mathbf{k}) - \delta \mathbf{k} - c(\mathbf{v}_0))$$

(This vector can be used to improve on \mathbf{D} – more on that in a second).

So far, this implies that we can write

$$\rho \mathbf{v}_1 = u(c(\mathbf{v}_0)) + (\mathbf{D}\mathbf{v}_1) \cdot \mathbf{s}_0$$

where the dot indicates element-by-element multiplication.

- ▶ We are close to a linear system though!
- Thus we will use this trick:
 - 7. Create the $N \times N$ matrix $\mathbf{S}_0 = diag(\mathbf{s_0})$

That is

$$\mathbf{S} = egin{pmatrix} s_1 & 0 & \dots & 0 \ 0 & s_2 & \dots & 0 \ dots & \ddots & \ddots & dots \ 0 & \dots & 0 & s_N \end{pmatrix},$$

8. Then we have

$$\rho \mathbf{v}_1 = u(c(\mathbf{v}_0)) + (\mathbf{D}\mathbf{v}_1) \cdot \mathbf{s}_0
= u(c(\mathbf{v}_0)) + \mathbf{S}_0 \mathbf{D}\mathbf{v}_1$$

9. This is a linear system. Thus, manipulate

$$(
ho \mathbf{I} - \mathbf{S}_0 \mathbf{D}) \mathbf{v}_1 = u(c(\mathbf{v}_0))$$

10. Lastly

$$\mathbf{v}_1 = (
ho \mathbf{I} - \mathbf{S}_0 \mathbf{D})^{-1} u(c(\mathbf{v}_0))$$

11. Generally

$$\mathbf{v}_{n+1} = (\rho \mathbf{I} - \mathbf{S}_n \mathbf{D})^{-1} u(c(\mathbf{v}_n))$$



Or even more generally

$$\mathbf{v}_{n+1} = ((\rho + 1/\Gamma)\mathbf{I} - \mathbf{S}_n\mathbf{D})^{-1}[u(c(\mathbf{v}_n)) + \mathbf{v}_n/\Gamma]$$

for Γ very large (my experience: $\Gamma = \infty$ is fastest, but set lower if convergence issues arise)

In matlab always use backslash operator to calculate $\mathbf{x} = \mathbf{A}^{-1}\mathbf{b}$. I.e. $\mathbf{x} = \mathbf{A} \setminus \mathbf{b}$

We are talking very substantial speed/robustness gains here. Perhaps by a factor of 1,000.

The implicit method: Improvement trick I

- ▶ Yesterday we created the matrix **D** as central differences
- ▶ We can do better. In particular, \mathbf{s}_n tells us where the economy is drifting for each $k_i \in \mathbf{k}$
- ▶ So trick one is to use forward differences for all

$$\{k_i \in \mathbf{k} : s_i > 0\}$$

and backward differences for all

$$\{k_i \in \mathbf{k} : s_i < 0\}$$

This leads to

$$\mathbf{v}_{n+1} = ((\rho + 1/\Gamma)\mathbf{I} - \mathbf{S}_n \mathbf{D}_n)^{-1} [u(c(\mathbf{v}_n)) + \mathbf{v}_n/\Gamma]$$



The implicit method: Improvement trick II

► Inspect the matrix

$$((\rho+1/\Gamma)\mathbf{I}-\mathbf{S}_n\mathbf{D}_n),$$

and notice that all matrices are super sparse!

- So declaring them as sparse will free up a lot of memory and give you enormous speed gains too (this is particularly true for problems with N > 200 or so. Below that it doesn't really matter).
- ► Never declare any of these matrices as anything else than sparse! Use commands as speye and spdiags
- ▶ **Don't** be too concerned about loops. That doesn't seem to be what can clog these systems.