

Lecture 3

Growth Model: Dynamic Optimization in Continuous Time

Macroeconomics EC417

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Growth Model in Continuous Time

- **Preferences:** representative household with utility function

$$\int_0^{\infty} e^{-\rho t} u(c(t)) dt$$

$\rho \geq 0$ = discount *rate* (as opposed to β = discount *factor*)

- **Technology:**

$$y(t) = f(k(t)), \quad c(t) + i(t) = y(t)$$

$$\dot{k}(t) = i(t) - \delta k(t), \quad c(t) \geq 0, \quad k(t) \geq 0$$

where $\dot{k}(t) = \frac{\partial k(t)}{\partial t}$

- **Endowments:** \hat{k}_0 of capital at $t = 0$
- Pareto optimal allocation solves

$$V(\hat{k}_0) = \max_{c(t)_{t=0}^{\infty}} \int_0^{\infty} e^{-\rho t} u(c(t)) dt \quad \text{s.t.}$$

$$\dot{k}(t) = f(k(t)) - \delta k(t) - c(t), \quad k(0) = \hat{k}_0$$

Hamiltonians

- Pretty much all deterministic optimal control problems in continuous time can be written as

$$V(\hat{x}_0) = \max_{\alpha(t)_{t=0}^{\infty}} \int_0^{\infty} e^{-\rho t} r(x(t), \alpha(t)) dt$$

subject to the law of motion for the state

$$\dot{x}(t) = g(x(t), \alpha(t)) \text{ and } \alpha(t) \in A$$

for $t \geq 0$, $x(0) = \hat{x}_0$ given.

- $\rho \geq 0$: discount rate
- $x \in X \subseteq \mathbb{R}^m$: state vector
- $\alpha \in A \subseteq \mathbb{R}^k$: control vector
- $r : X \times A \rightarrow \mathbb{R}$: instantaneous return function

Example: Growth Model

$$V(\hat{k}_0) = \max_{c(t)_{t=0}^{\infty}} \int_0^{\infty} e^{-\rho t} u(c(t)) dt \quad \text{s.t.}$$

$$\dot{k}(t) = f(k(t)) - \delta k(t) - c(t), \quad k(0) = \hat{k}_0$$

- Here the state is $x = k$ and the control $\alpha = c$
- $r(x, \alpha) = u(\alpha)$
- $g(x, \alpha) = f(x) - \delta x - \alpha$

Hamiltonian: General Formulation

- Consider the general optimal control problem two slides back.
- Can obtain necessary and sufficient conditions for an optimum using the following procedure (“cookbook”)
- Current-value Hamiltonian

$$\mathcal{H}(x, \alpha, \lambda) = r(x, \alpha) + \lambda g(x, \alpha).$$

- $\lambda \in \mathbb{R}^m$: “co-state”

Hamiltonian: General Formulation

Necessary and sufficient conditions:

$$\mathcal{H}_\alpha(x(t), \alpha(t), \lambda(t)) = 0 \quad (1)$$

$$\dot{x}(t) = g(x(t), \alpha(t)) \quad (2)$$

$$\dot{\lambda}(t) = \rho\lambda(t) - \mathcal{H}_x(x(t), \alpha(t), \lambda(t)) \quad (3)$$

for all $t \geq 0$.

- Initial value for state variable(s): $x(0) = \hat{x}_0$.
- Boundary condition (transversality condition) for co-state $\lambda(t)$

$$\lim_{T \rightarrow \infty} e^{-\rho T} \lambda(T) x(T) = 0.$$

- Note: initial value of the co-state $\lambda(0)$ not predetermined.

Where Does This Come From?

- Eq. 1 just says that $\alpha(t)$ maximizes \mathcal{H} for all t .
- Eq. 2 is the law of motion for the state.
- Eq. 3 is the law of motion for the co-state.¹

Interpretation of the law of motion of the co-state (Acemoglu):

- $\lambda(t)$ is the value of the stock $x(t)$.
- $-\dot{\lambda}(t)$ is the depreciation in the value of the stock due to small increase in $x(t)$.
- The value of increasing $x(t)$ is the negative of the RHS of 3.
- Eq. 3 says the two should be equal.

¹Comes from Pontryagin's Maximum Principle. To see where it comes from, can set up a "Lagrangian" for the entire problem, use integration by parts on the resource constraint, and take FOCs for $\alpha(t)$ and $x(t)$.

Example: Neoclassical Growth Model

- Recall: $r(x, \alpha) = u(\alpha)$ and $g(x, \alpha) = f(x) - \delta x - \alpha$
- Using the “cookbook”

$$\mathcal{H}(k, c, \lambda) = u(c) + \lambda[f(k) - \delta k - c]$$

- We have

$$\mathcal{H}_c(k, c, \lambda) = u'(c) - \lambda$$

$$\mathcal{H}_k(k, c, \lambda) = \lambda(f'(k) - \delta)$$

- Therefore conditions for optimum are:

$$\dot{\lambda} = \lambda(\rho + \delta - f'(k))$$

$$\dot{k} = f(k) - \delta k - c \tag{ODE}$$

$$u'(c) = \lambda$$

with $k(0) = \hat{k}_0$ and $\lim_{T \rightarrow \infty} e^{-\rho T} \lambda(T) k(T) = 0$.

Example: Neoclassical Growth Model

- Interpretation: continuous time Euler equation
- In discrete time

$$\lambda_t = \beta \lambda_{t+1} (f'(k_{t+1}) + 1 - \delta)$$

$$k_{t+1} = f(k_t) + (1 - \delta)k_t - c_t$$

$$u'(c_t) = \lambda_t$$

- (ODE) is continuous-time analogue

Phase Diagrams

- How to analyze (ODE)? In one-dimensional case (scalar x): use phase-diagram
- Two possible phase-diagrams:
 - (i) in (λ, k) -space: more general strategy.
 - (ii) in (c, k) -space: nicer in terms of the economics.
- For (i), use $u'(c) = \lambda$ or $c = (u')^{-1}(\lambda)$ to write (ODE) as

$$\begin{aligned}\dot{\lambda} &= \lambda(\rho + \delta - f'(k)) \\ \dot{k} &= f(k) - \delta k - (u')^{-1}(\lambda)\end{aligned}\tag{ODE'}$$

with $k(0) = k_0$ and $\lim_{T \rightarrow \infty} e^{-\rho T} \lambda(T) k(T) = 0$.

- Exercise: draw phase-diagram in (λ, k) -space.

Phase Diagrams

- For (ii), assume CRRA utility, not nec. but simplifies algebra:

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

- To substitute $\dot{\lambda}$ out of ODE take logs and diff. wrt t :

$$c^{-\sigma} = \lambda \quad \Rightarrow \quad -\sigma \log c(t) = \log \lambda(t) \quad \Rightarrow \quad -\sigma \frac{\dot{c}}{c} = \frac{\dot{\lambda}}{\lambda}$$

- Therefore write (ODE) as

$$\begin{aligned} \frac{\dot{c}}{c} &= \frac{1}{\sigma}(f'(k) - \rho - \delta) \\ \dot{k} &= f(k) - \delta k - c \end{aligned} \tag{ODE''}$$

with $k(0) = k_0$ and $\lim_{T \rightarrow \infty} e^{-\rho T} c(T)^{-\sigma} k(T) = 0$.

Steady State

- In steady state $\dot{k} = \dot{c} = 0$. Therefore

$$f'(k^*) = \rho + \delta$$

$$c^* = f(k^*) - \delta k^*$$

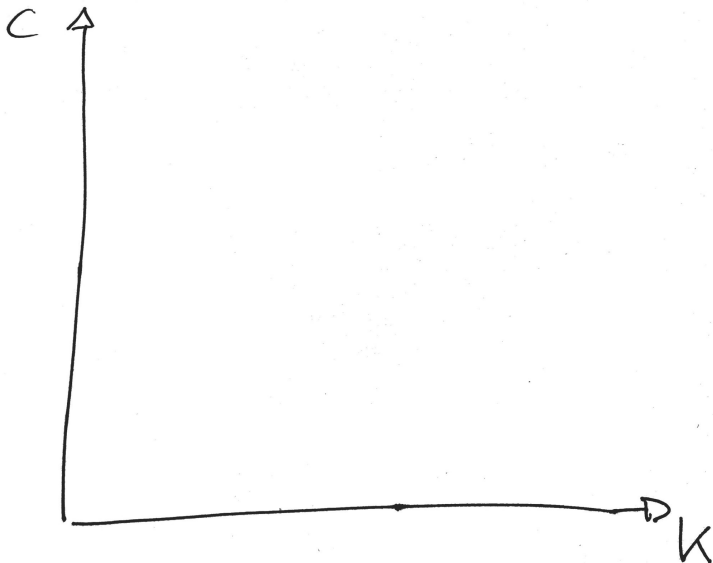
- Same as in discrete time with $\beta = 1/(1 + \rho)$.
- For example, if $f(k) = Ak^\alpha, \alpha < 1$. Then

$$k^* = \left(\frac{\alpha A}{\rho + \delta} \right)^{\frac{1}{1-\alpha}}$$

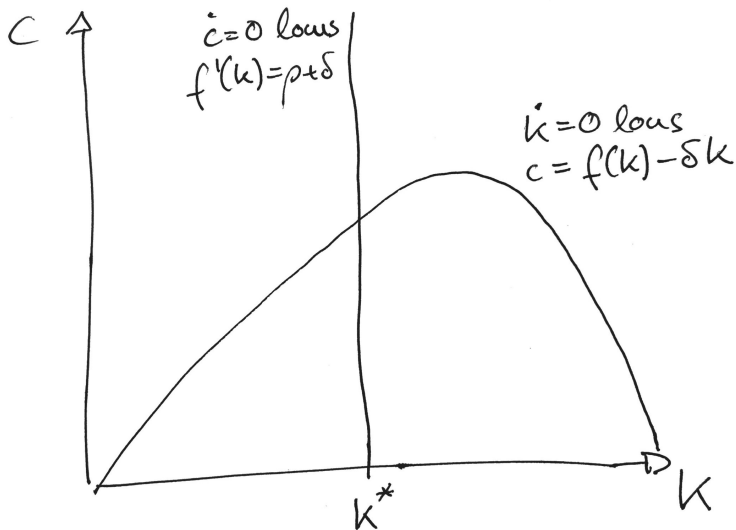
Phase Diagram

- See graph drawn by hand or Figure 8.1 in Acemoglu's textbook
- Steps for drawing phase diagrams:
 1. draw figure in phase plane, here in (c, k) space
 2. draw $\dot{c} = 0$ and $\dot{k} = 0$ loci (loci = plural of locus)
 3. dynamics away from $\dot{c} = 0$ and $\dot{k} = 0$ loci
 4. use loci to split phase plane into areas and find dynamics in these areas using step 3
 5. draw arrows indicating dynamics
 6. draw trajectories for different initial conditions and find saddle path (if there is one)

Step 1: draw figure in phase plane



Step 2: draw $\dot{c} = 0$ and $\dot{k} = 0$ loci



Step 3: dynamics away from $\dot{c} = 0$ and $\dot{k} = 0$ loci

- Recall

$$\begin{aligned}\frac{\dot{c}}{c} &= \frac{1}{\sigma}(f'(k) - \rho - \delta) \\ \dot{k} &= f(k) - \delta k - c\end{aligned}\tag{ODE''}$$

with $k(0) = k_0$ and $\lim_{T \rightarrow \infty} e^{-\rho T} c(T)^{-\sigma} k(T) = 0$.

- Dynamics of k away from $\dot{k} = 0$ locus:

$$\dot{k} > 0 \quad \Leftrightarrow \quad f(k) - \delta k - c > 0 \quad \Leftrightarrow \quad c < f(k) - \delta k$$

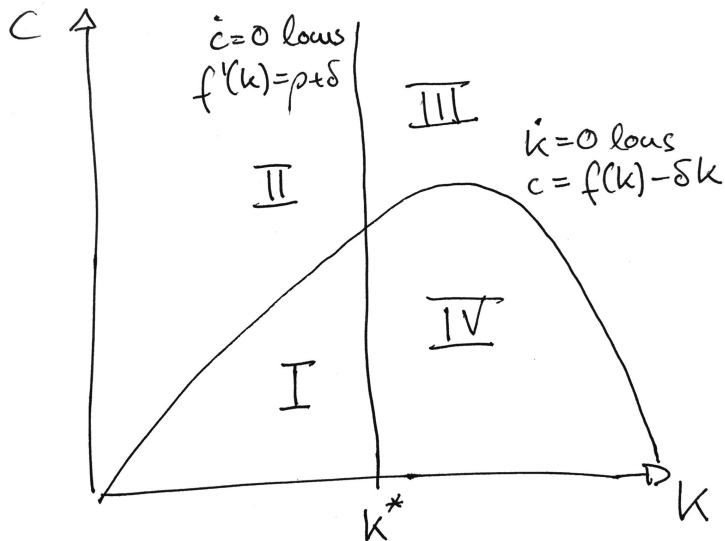
$\Rightarrow \dot{k} > 0$ below $\dot{k} = 0$ locus and $\dot{k} < 0$ above $\dot{k} = 0$ locus

- Dynamics of c away from $\dot{c} = 0$ locus:

$$\dot{c} > 0 \quad \Leftrightarrow \quad f'(k) - \rho - \delta > 0 \quad \Leftrightarrow \quad f'(k) > \rho + \delta \quad \Leftrightarrow \quad k < k^*$$

$\Rightarrow \dot{c} > 0$ to left of $\dot{c} = 0$ locus and $\dot{c} < 0$ to right of $\dot{c} = 0$ locus

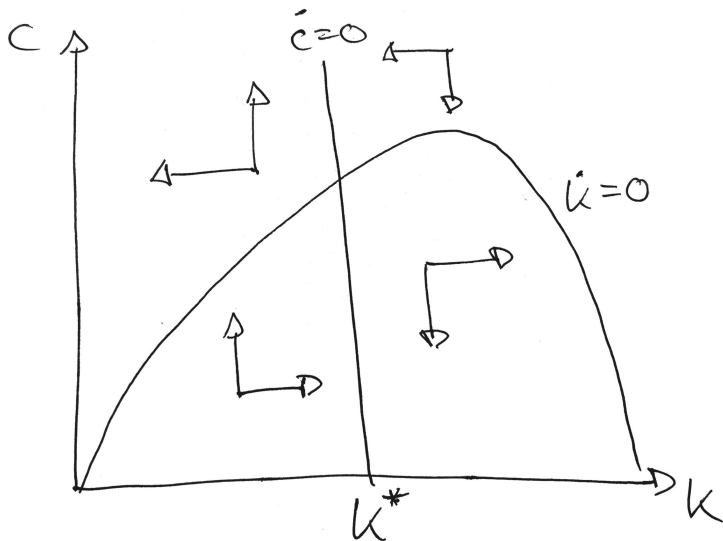
Step 4: use loci to split phase plane into areas ...



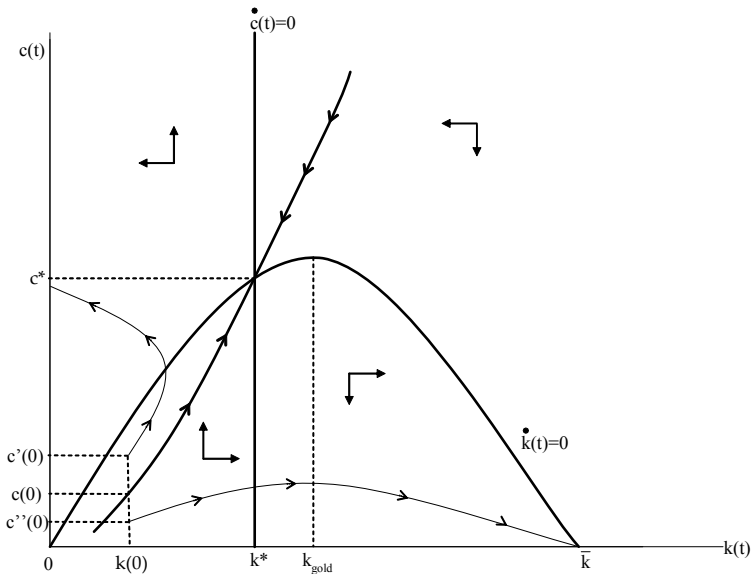
Step 4: ... and find dynamics in areas using step 3

- Area I: left of $\dot{c} = 0$ locus and below $\dot{k} = 0$ locus: $\dot{c} > 0, \dot{k} > 0$
- Area II: left of $\dot{c} = 0$ locus and above $\dot{k} = 0$ locus: $\dot{c} > 0, \dot{k} < 0$
- Area III: right of $\dot{c} = 0$ locus and below $\dot{k} = 0$ locus: $\dot{c} < 0, \dot{k} > 0$
- Area IV: right of $\dot{c} = 0$ locus and above $\dot{k} = 0$ locus: $\dot{c} < 0, \dot{k} < 0$

Step 5: draw arrows indicating dynamics



Step 6: trajectories & saddle path (Acemoglu Fig 8.1)



Phase Diagram

- Obtain saddle path.
- Prove stability of steady state.
- Important: saddle path is **not** a “knife edge” case in the sense that the system only converges to steady state if $(c(0), k(0))$ happens to lie on the saddle path and diverges for all other initial conditions.
- In contrast to the state variable $k(t)$, $c(t)$ is a “jump variable.” That is, $c(0)$ is free and **always** adjusts so as to lie on the saddle path.

Violations of Transversality Condition

- **Question:** how do you know that trajectories with $c(0)$ off the saddle path violate the transversality condition?
- See Acemoglu, chapter 8 “The Neoclassical Growth Model” section 5 “Transitional Dynamics”
 - if $c(0)$ below saddle path, $k(t) \rightarrow k_{\max}$ and $c(t) \rightarrow 0$
 - if $c(0)$ above saddle path, $k(t) \rightarrow 0$ in finite time while $c(t) > 0$. Violates feasibility.
 - local analysis/linearization gives same answer. Next lecture.
 - notes that most rigorous and straightforward way is to use the fact that concave problems have unique solution (his Theorem 7.14)

Numerical Solution: Finite-Diff. Methods

- By far the simplest and most transparent method for numerically solving differential equations.
- Approximate $k(t)$ and $c(t)$ at N discrete points in the time dimension, $t^n, n = 1, \dots, N$. Denote distance between grid points by Δt .
- Use short-hand notation $k^n = k(t^n)$.
- Approximate derivatives

$$\dot{k}(t^n) \approx \frac{k^{n+1} - k^n}{\Delta t}$$

- Approximate (ODE'') as

$$\begin{aligned} \frac{c^{n+1} - c^n}{\Delta t} \frac{1}{c^n} &= \frac{1}{\sigma} (f'(k^n) - \rho - \delta) \\ \frac{k^{n+1} - k^n}{\Delta t} &= f(k^n) - \delta k^n - c^n \end{aligned}$$

Finite-Diff. Methods/Shooting Algorithm

- Or

$$\begin{aligned}c^{n+1} &= \Delta t c^n \frac{1}{\sigma} (f'(k^n) - \rho - \delta) + c^n \\k^{n+1} &= \Delta t (f(k^n) - \delta k^n - c^n) + k^n\end{aligned}\tag{FD}$$

with $k^0 = k_0$ given.

- Exercise: draw phase diagram/saddle path in MATLAB.
- Assume $f(k) = Ak^\alpha$, $A = 1$, $\alpha = 0.3$, $\sigma = 2$, $\rho = \delta = 0.05$, $k_0 = \frac{1}{2}k^*$, $\Delta t = 0.1$, $N = 700$.
- Algorithm:
 - (i) guess c^0
 - (ii) obtain (c^n, k^n) , $n = 1, \dots, N$ by running (FD) forward in time.
 - (iii) If the sequence converges to (c^*, k^*) , then you have obtained the correct saddle path. If not, back to (i) and try different c^0 .
- This is called a “shooting algorithm”