

# Markov Decision Processes in Economics

Stoc Proc 25-26, Based on Brock-Mirman (1972, JET)

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## A Classic Problem: Growth with Uncertainty

- Each period, the economy produces output using last period's capital and today's productivity.
- Productivity can be *high* or *low* and changes over time in a random but persistent way.
- A planner chooses how much of today's output to **consume** and how much to **save** as new capital for tomorrow.
- The tradeoff: enjoy consumption now vs. invest to raise uncertain future production.
- Goal: choose consumption/saving each period to maximize society's discounted well-being over time.

## Formal Setup (Brock–Mirman, 1972)

- **State variables:** capital  $K_t$ , productivity  $z_t$ .
- **Production:**  $Y_t = z_t f(K_t)$ .
- **Resource constraint:**  $Y_t = C_t + K_{t+1}$  (no depreciation for simplicity; include  $\delta$  if needed).
- **Shock dynamics:**  $z_{t+1} \sim P(\cdot | z_t)$  (finite-state Markov or AR(1) in logs).
- **Objective:**

$$\max_{\{C_t\}_{t \geq 0}} \mathbb{E} \left[ \sum_{t=0}^{\infty} \beta^t u(C_t) \right], \quad 0 < \beta < 1.$$

- **Control:** choose  $C_t$  (equivalently choose  $K_{t+1} = z_t f(K_t) - C_t$ ) each period.



# From Stochastic Processes to Markov Chains

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## Without Control: The Shock Process

- Productivity evolves randomly:  $z_{t+1}$  depends on  $z_t$ .
- This sequence  $\{z_t\}$  is a stochastic process.
- To model persistence, assume  $z_t$  follows a Markov chain.

# Markov Property

## Definition

A process  $\{z_t\}$  is Markov if

$$P(z_{t+1} \mid z_t, z_{t-1}, \dots) = P(z_{t+1} \mid z_t).$$

- In Brock–Mirman: productivity has memory only of the last period.
- Example: 2-state productivity  $\{H, L\}$  with transition matrix

$$P = \begin{bmatrix} p & 1-p \\ 1-q & q \end{bmatrix}.$$

# Expected Rewards with a Markov Chain

- For a fixed policy, the induced process is a DTMC.
- DTMC theory: stationary distributions allow computation of long-run averages.
- With discounting, expected reward is

$$\mathbb{E} \left[ \sum_{t=0}^{\infty} \beta^t u(C_t) \right].$$



## **Adding Control: The MDP Framework**

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# Adding Back Control

- State:  $(K_t, z_t)$ .
- Action: consumption choice  $C_t$  (or equivalently next capital  $K_{t+1}$ ).
- Transition:

$$K_{t+1} = z_t f(K_t) - C_t, \quad z_{t+1} \sim P(\cdot | z_t).$$

- Reward:  $u(C_t)$ .

## Definition: Infinite-Horizon MDP

- State space  $S$ , action space  $A(s)$ .
- Transition kernel  $P(s' \mid s, a)$ .
- Reward function  $r(s, a)$ .
- Discount factor  $\beta \in (0, 1)$ .

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### Policy

A stationary policy  $\pi : S \rightarrow A$  maps states to actions.

# Value Functions

- Value of policy  $\pi$ :

$$V^{\pi}(s) = \mathbb{E}_s^{\pi} \left[ \sum_{t=0}^{\infty} \beta^t r(s_t, a_t) \right].$$

- Optimal value:

$$V^*(s) = \sup_{\pi} V^{\pi}(s).$$

# Bellman Optimality

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# Bellman Optimality Equation

## Theorem (Bellman)

There exists an optimal stationary policy  $\pi^*$  and

$$V^*(s) = \max_{a \in A(s)} \left\{ r(s, a) + \beta \sum_{s'} P(s' \mid s, a) V^*(s') \right\}.$$

# Sketch of Proof

1. Define Bellman operator  $T$ :

$$(TV)(s) = \max_a \{r(s, a) + \beta \sum_{s'} P(s' | s, a) V(s')\}.$$

2. Show  $T$  is a contraction under sup norm.
3. Banach fixed point theorem  $\implies$  unique  $V^*$ .
4. Greedy policy wrt  $V^*$  is optimal.



## **Application: Solving Brock–Mirman**

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# Bellman Equation for Growth Model

$$V(K, z) = \max_C \{u(C) + \beta \mathbb{E}[V(K', z') \mid z]\},$$

subject to  $K' = zf(K) - C$ .

- Optimal consumption-saving policy derived from Bellman equation.
- Shocks are persistent  $\implies$  precautionary saving motive.
- Links to modern RBC and DSGE models.

# What the Bellman Equation Delivers in Brock–Mirman

- **Closed-form policy:** With log utility and Cobb–Douglas  $f(K)$ , optimal consumption is a constant fraction of output:

$$C_t = (1 - \alpha\beta) z_t K_t^\alpha.$$

- **Markov sufficiency:** Optimal action depends only on current state  $(K_t, z_t)$ .
- **Role of parameters:**
  - Higher patience  $\beta \Rightarrow$  more saving.
  - Higher productivity shock  $z_t \Rightarrow$  proportional rise in both  $C_t$  and  $K_{t+1}$ .
- **Big picture:** Dynamic programming makes stochastic growth tractable; this recursion became the prototype for modern RBC models.