

# Honors - Economic Analysis III

## Lecture 6: Dynamic Programming I

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# This lecture

- Motivate dynamic programming approach
  - Neoclassical model under uncertainty  $\rightarrow$  RBC model
- Terminology
  - State variables
  - Value function
  - Policy function
  - Markov chain
- Next: (i) Methods, (ii) Labor supply, (iii) RBC model

# Environment - Centralized / Deterministic

- *Time* - Discrete  $t = 0, 1, 2 \dots$
- *Agents* - Representative household with  $N$  workers
- *Goods* - One good can either be used for consumption or investment

$$c_t + i_t = y_t$$

- *Endowments* - Household owns the initial capital stock  $k_0$
- *Preferences* - Utility of the household at date 0 is

$$\sum_{t=0}^{\infty} \beta^t u(c_t) \quad , \quad \beta \in (0, 1)$$

- *Technology* - Constant returns to scale production technology  $y_t = f(k_t)$ . Capital depreciates at rate  $\delta$

$$k_{t+1} = (1 - \delta)k_t + i_t \quad , \quad \delta \in [0, 1]$$

# Problem

Household chooses sequences of  $\{c_t, k_{t+1}\}_{t=0}^{\infty}$

$$\max \sum_{t=0}^{\infty} \beta^t u(c_t)$$

subject to the series of constraints

$$c_t + k_{t+1} \leq f(k_t) + (1 - \delta)k_t \quad , \quad t = 0, 1, 2, \dots$$

and initial conditions

$$k_0 > 0$$

## Environment - Centralized / Stochastic

- *Time* - Discrete  $t = 0, 1, 2 \dots$
- *Agents* - Representative household with  $N$  workers
- *Goods* - One good can either be used for consumption or investment

$$c_t + i_t = y_t$$

- *Endowments* - Household owns the initial capital stock  $k_0$
- *Preferences* - Utility of the household at date 0 is

$$\mathbb{E}_0 \left[ \sum_{t=0}^{\infty} \beta^t u(c_t) \right] \quad , \quad \beta \in (0, 1)$$

- *Technology* - Constant returns to scale production technology  $y_t = A_t f(k_t)$ , where given  $A_0$ ,  $\{A_t\}_{t=1}^{\infty}$  is given by *stochastic process*:

$$\log A_{t+1} = (1 - \rho) \log \bar{A} + \rho \log A_t + \underbrace{\varepsilon_{t+1}}_{\text{'Shock'}}, \quad \varepsilon_{t+1} \sim N(0, \sigma_\varepsilon)$$

Capital depreciates at rate  $\delta$

# Why?

## Kydland and Prescott (1982)

- In the data we observe large, persistent, fluctuations in  $A_t$

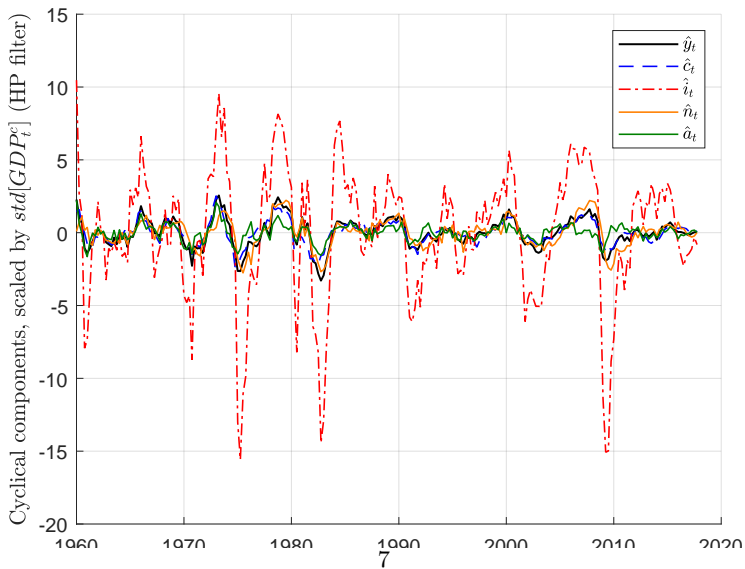
$$Y_t = A_t K_t^\alpha N_t^{1-\alpha}$$
$$\log Y_t = \alpha \log K_t + (1 - \alpha) \log N_t + \log A_t.$$

- **Q:** Can ‘shocks’ to  $A_t$  account for business cycles in the NC model?

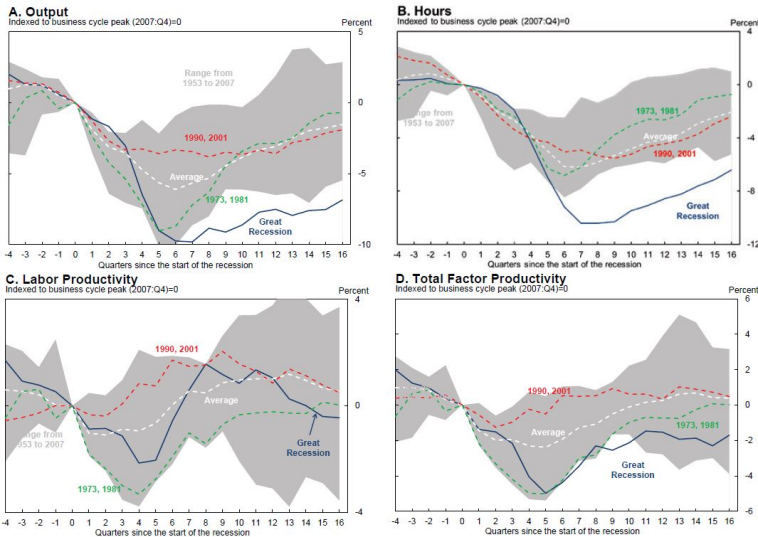
## Why do we care?

- As we learned in Lecture 4 ... NC model: (i) *Always in equilibrium*, (ii) *Welfare theorems hold*
- 1970s ‘Keynesian’ view: Recessions represent the economy being ‘out of equilibrium’ in some way. Government can intervene.
- **Normative** - If the answer is ‘yes’ then recessions are the economy’s natural responses to exogenous shocks
- **Positive** - We have a quantitative theory of business cycles!

# Business cycles - US data



# Business cycles - US data



Fernald (2014) - Productivity and Potential Output Before, During, and After the Great Recession -



## Business cycles - US data

		Volatility $std[\hat{x}_t]/std[\hat{y}_t]$	Covariance $corr(\hat{x}_t, \hat{y}_t)$	Persistence $corr(\hat{x}_t, \hat{x}_{t-1})$
Output (GDP)	$\hat{y}_t$	1	1	0.86
Consumption	$\hat{c}_t$	0.81	0.87	0.87
Investment	$\hat{i}_t$	4.52	0.90	0.83
Hours	$\hat{n}_t$	0.98	0.84	0.86

- **Consumption** - Less volatile than output
- **Investment** - Much volatile than output
- **Hours** - As volatile as output
- All series highly correlated with output

## Problem in a not very useful format

Household chooses sequences of  $\{c_t, k_{t+1}\}_{t=0}^{\infty}$

$$\max \mathbb{E}_0 \left[ \sum_{t=0}^{\infty} \beta^t u(c_t) \right]$$

subject to the sequence of constraints      Set  $\delta = 1$

$$c_t + k_{t+1} \leq e^{a_t} f(k_t) \quad , \quad t = 0, 1, 2, \dots$$

and initial conditions

$$k_0 > 0, \quad a_0$$

and stochastic process for  $a_t = \log A_t - \log \bar{A}$

$$a_{t+1} = \rho a_t + \varepsilon_{t+1} \quad , \quad \varepsilon_{t+1} \sim N(0, \sigma_\varepsilon)$$

## Concept - State

- A *state*  $s_t$  is a finite vector of variables pre-determined at date- $t$ 
  - Pre-determined - Values are realized before actions of saving / consumption occur
- A *history*  $s^t$  is a  $t$ -period sequence of past states

$$s^t = (s_0, s_1, \dots, s_{t-1}, s_t) = (s^{t-1}, s_t)$$

- Probability distribution  $\pi(s^t) \in [0, 1]$  is defined over histories

$$\pi(s^t) = \pi(s_t, s^{t-1}) = \pi(s_t | s^{t-1}) \pi(s^{t-1}) = \pi(s_t | s^{t-1}) \pi(s_{t-1} | s^{t-2}) \dots \pi(s_1 | s^0) \pi(s_0)$$

- What is in the state vector?
  - Good question!
  - For now we remain agnostic.
  - Use  $s^t$  as a way for accounting in the household problem
  - *Dynamic programming* approach will answer this question precisely!

## Concept - State

- A *state*  $s_t$  is a finite vector of variables *pre-determined* at date- $t$
- A *history*  $s^t$  is a  $t$ -period sequence of past states

$$s^t = (s_0, s_1, \dots, s_{t-1}, s_t) = (s^{t-1}, s_t)$$

- Probability distribution  $\pi(s^t) \in [0, 1]$  is defined over *histories*

$$\pi(s^t) = \pi(s_t, s^{t-1}) = \pi(s_t | s^{t-1}) \pi(s^{t-1}) = \pi(s_t | s^{t-1}) \pi(s_{t-1} | s^{t-2}) \dots \pi(s_1 | s^0)$$

- Stationarity

- We will study models where  $\pi(s_{t+1} | s^t)$  depends only on  $s_t$
- If  $s_t = \text{'Low'}$ , then no matter what date  $t$  is we have the same

$$\pi(s_{t+1} = \text{'High'} | s_t = \text{'Low'})$$

- The state is a *Markov process* - The probability distribution over states tomorrow, depends only on the state today

## Concept - State

- A *state*  $s_t$  is a finite vector of variables *pre-determined* at date- $t$
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$$s^t = (s_0, s_1, \dots, s_{t-1}, s_t) = (s^{t-1}, s_t)$$

- Probability distribution  $\pi(s^t) \in [0, 1]$  is defined over *histories*

$$\pi(s^t) = \pi(s_t, s^{t-1}) = \pi(s_t | s^{t-1}) \pi(s^{t-1}) = \pi(s_t | s_{t-1}) \pi(s_{t-1} | s_{t-2}) \dots \pi(s_1 | s_0)$$

- Stationarity

- We will study models where  $\pi(s_{t+1} | s_t)$  does not depend on  $t$
- If  $s_t = \text{'Low'}$ , then no matter what date  $t$  is we have the same

$$\pi(s_{t+1} = \text{'High'} | s_t = \text{'Low'})$$

- The state is a *Markov process* - The prob. distribution over states tomorrow, depends only on the state today

# Concept - State - Example

- States

$$a_t \in \{a^L, a^H\}$$

- Stochastic process - Consider a simple first-order *Markov process*

$$\pi_a(a^L|a^L) = \pi_a(a^H|a^H) = 0.90 \quad , \quad \text{and}$$

$$\pi_a(a^L|a^H) = \pi_a(a^H|a^L) = 0.10$$

- Initial condition

$$a_0 = a^H$$

- Probability distribution over states  $\pi_a(a^t|a_0)$ :

- What is  $\pi_a(a^t|a_0)$ , when  $a^t = (a^H, a^H, a^H)$ ?

$$\pi_a(a^t) = 0.90 \times 0.90 = 0.81$$

- What is  $\pi_a(a^t|a_0)$ , when  $a^t = (a^H, a^L, a^H)$ ?

$$\pi_a(a^t) = 0.10 \times 0.90 = 0.09$$

## Problem in a not very useful format

Household chooses sequences of  $\{c_t, k_{t+1}\}_{t=0}^{\infty}$

$$\max \mathbb{E}_0 \left[ \sum_{t=0}^{\infty} \beta^t u(c_t) \right]$$

subject to the series of constraints

$$c_t + k_{t+1} \leq e^{a_t} f(k_t) \quad , \quad t = 0, 1, 2, \dots$$

and initial conditions

$$k_0 > 0, \quad a_0$$

and stochastic process for  $a_t$

$$a_{t+1} = \rho a_t + \varepsilon_{t+1} \quad , \quad \varepsilon_{t+1} \sim N(0, \sigma_\varepsilon)$$

## State-contingent Problem

Chooses **state-contingent** sequences  $\{c_t(s^t), k_{t+1}(s^t)\}_{t=0, \forall s^t}^{\infty}$

$$\max_{\{c_t(s^t), k_{t+1}(s^t)\}} \left[ \sum_{t=0}^{\infty} \sum_{s^t | s_0} \beta^t \pi(s^t | s_0) u(c_t(s^t)) \right]$$

subject to the series of **state-contingent** constraints

$$c_t(s^t) + k_{t+1}(s^t) \leq e^{a_t(s^t)} f(k_t(s^t)) \quad , \quad t = 0, 1, 2, \dots, \quad \forall s^t$$

and initial conditions

$$k_0(s_0) > 0 \quad , \quad a_0(s_0)$$

and stochastic process for  $a_t$

$$a_{t+1}(s^{t+1}) = \rho a_t(s^t) + \varepsilon_{t+1} \quad , \quad \varepsilon_{t+1} \sim N(0, \sigma_{\varepsilon})$$



## Problem - Lagrangean

- Constrained optimization problem

$$\mathcal{L} = \sum_{t=0}^{\infty} \sum_{s^t | s_0} \beta^t \pi(s^t | s_0) u(c_t(s^t)) \quad (1)$$

$$+ \sum_{t=0}^{\infty} \sum_{s^t | s_0} \lambda_t(s^t) \left[ e^{a_t(s^t)} f(k_t(s^t)) - c_t(s^t) - k_{t+1}(s^t) \right] \quad (2)$$

- First order necessary conditions

$$c_t(s^t) : \quad \lambda_t(s^t) = \pi(s^t | s_0) \beta^t u'(c_t(s^t))$$

$$k_{t+1}(s^t) : \quad \lambda_t(s^t) = \sum_{s_{t+1} | s^0} \lambda_{t+1}(s_{t+1}, s^t) f'(k_{t+1}(s^t))$$

- Combining conditions

$$\pi(s^t | s_0) u'(c_t(s^t)) = \beta \sum_{s_{t+1} | s^0} \pi(s^{t+1} | s_0) u'(c_{t+1}(s^{t+1})) f'(k_{t+1}(s^t))$$

## Problem - Lagrangean

- Combining conditions

$$\pi(s^t | s_0) u'(c_t(s^t)) = \beta \sum_{s^{t+1} | s_0} \pi(s_{t+1}, s^t | s_0) u'(c_{t+1}(s^{t+1})) f'(k_{t+1}(s^t))$$

- Conditional probabilities

$$\pi(s_{t+1}, s^t | s_0) = \pi(s_{t+1} | s^t) \pi(s^t | s_0)$$

- Using this

$$u'(c_t(s^t)) = \beta \sum_{s_{t+1} | s^t} \pi(s_{t+1} | s^t) u'(c_{t+1}(s^{t+1})) f'(k_{t+1}(s^t))$$

- More simply

$$u'(c_t(s^t)) = \beta \mathbb{E} \left[ u'(c_{t+1}(s^{t+1})) f'(k_{t+1}(s^t)) \middle| s^t \right]$$

# Equilibrium conditions

- For all  $t = 0, 1, 2, \dots$ , and for all  $s^t|s_0$

## 1. Euler equation

$$u'(c_t(s^t)) = \beta \sum_{s_{t+1}|s^t} \pi(s_{t+1}|s^t) u'(c_{t+1}(s^{t+1})) f'(k_{t+1}(s^t))$$

## 2. Resource constraint

$$c_t(s^t) + k_{t+1}(s^t) \leq e^{a_t(s^t)} f(k_t(s^t))$$

## 3. Transversality condition

$$\lim_{T \rightarrow \infty} \beta^T \pi(s^T|s_0) u'(c_T(s^T)) k_{T+1}(s^T) = 0$$

# Equilibrium conditions

- For all  $t = 0, 1, 2, \dots$ , and for all  $s^t | s_0$

## 1. Euler equation

$$u'(c_t(s^t)) = \beta \sum_{s^{t+1} | s^t} \pi(s_{t+1} | s^t) u'(c_{t+1}(s^{t+1})) f'(k_{t+1}(s^t))$$

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$$\lim_{T \rightarrow \infty} \beta^T \mathbb{E} \left[ u'(c_T) k_{T+1} \middle| s_0 \right] = 0$$

# Equilibrium conditions

- For all  $t = 0, 1, 2, \dots$ , and for all  $s^t | s_0$

## 1. Euler equation

$$u'(c_t(s^t)) = \beta \sum_{s_{t+1} | s^t} \pi(s_{t+1} | s^t) u'(c_{t+1}(s^{t+1})) f'(k_{t+1}(s^t))$$

## 2. Resource constraint

$$c_t(s^t) + k_{t+1}(s^t) \leq e^{a_t(s^t)} f(k_t(s^t))$$

## 3. Transversality condition

$$\lim_{T \rightarrow \infty} \beta^T \mathbb{E} \left[ u'(c_T) k_{T+1} \middle| s_0 \right] = 0$$

- Still lots of questions!
  - State variables: What is in  $s_t$ ?
  - How do decisions depend on  $s^t$  and  $t$ ? Is it  $c_t(s^t)$  or  $c_t(s_t)$  or  $c(s_t)$ ?
  - How to solve for  $c_t(s^t)$ ,  $k_{t+1}(s^t)$ ?

# Value function

- The *value function*  $V_t(s^t)$  is the expected present discounted value of the household's utility under the *optimal policy* for consumption and capital, where this value is computed *after* the realization of the history  $s^t$ , but *before* the choice of  $c_t(s^t)$  and  $k_{t+1}(s^t)$
- Period 0, state  $s_0$  value function:

$$V_0(s_0) := \max_{\{c_t(s^t), k_{t+1}(s^t)\}} \left[ \sum_{t=0}^{\infty} \sum_{s^t | s_0} \beta^t \pi(s^t | s_0) u(c_t(s^t)) \right]$$

subject to the series of state-contingent constraints

$$c_t(s^t) + k_{t+1}(s^t) = e^{a_t(s^t)} f(k_t(s^t)) \quad , \quad \forall t \geq 0, \forall s^t | s^0$$

# Value function

- Period 0, state  $s_0$  value function: Split up into  $t = 0$  and  $t \geq 1$

$$V_0(s_0) = \max_{c_0(s_0), k_1(s_0)} u(c_0(s_0)) \\ + \left\{ \max_{\{c_t(s^t), k_{t+1}(s^t)\}} \left[ \sum_{t=1}^{\infty} \sum_{s^t | s_0} \beta^t \pi(s^t | s_0) u(c_t(s^t)) \right] \right\}$$

subject to the series of state-contingent constraints

$$c_0(s_0) + k_1(s_0) = e^{a_0(s_0)} f(k_0(s_0))$$

$$c_t(s^t) + k_{t+1}(s^t) = e^{a_t(s^t)} f(k_t(s^t)) \quad , \quad \forall t \geq 1, \forall s^t | s_1, s_0$$

# Value function

- Period 0, state  $s_0$  value function:  $\pi(s^t|s_0) = \pi(s^t|s_1)\pi(s_1|s_0)$

$$V_0(s_0) = \max_{c_0(s_0), k_1(s_0)} u(c_0(s_0)) \\ + \left\{ \max_{\{c_t(s^t), k_{t+1}(s^t)\}} \left[ \sum_{t=1}^{\infty} \sum_{s^t|s_0} \beta^t \pi(s^t|s_1) \pi(s_1|s_0) u(c_t(s^t)) \right] \right\}$$

subject to the series of state-contingent constraints

$$c_0(s_0) + k_1(s_0) = e^{a_0(s_0)} f(k_0(s_0))$$

$$c_t(s^t) + k_{t+1}(s^t) = e^{a_t(s^t)} f(k_t(s^t)) \quad , \quad \forall t \geq 1, \forall s^t|s_1, s_0$$



## Value function

- Period 0, state  $s_0$  value function:  $\sum_{s^t|s_0} = \sum_{s^t|s_1} \sum_{s_1|s_0}$

$$V_0(s_0) = \max_{c_0(s_0), k_1(s_0)} u(c_0(s_0)) \\ + \sum_{s_1|s_0} \pi(s_1|s_0) \left\{ \max_{\{c_t(s^t), k_{t+1}(s^t)\}} \left[ \sum_{t=1}^{\infty} \sum_{s^t|s_1} \beta^t \pi(s^t|s_1) u(c_t(s^t)) \right] \right\}$$

subject to the series of state-contingent constraints

$$c_0(s_0) + k_1(s_0) = e^{a_0(s_0)} f(k_0(s_0))$$

$$c_t(s^t) + k_{t+1}(s^t) = e^{a_t(s^t)} f(k_t(s^t)) \quad , \quad \forall t \geq 1, \forall s^t|s_1, s_0$$

# Value function

- Period 0, state  $s_0$  value function:  $\sum_{t=1}^{\infty} \beta^t = \beta \sum_{t=0}^{\infty} \beta^t$

$$V_0(s_0) = \max_{c_0(s_0), k_1(s_0)} u(c_0(s_0)) \\ + \beta \sum_{s_1|s_0} \pi(s_1|s_0) \left\{ \max_{\{c_t(s^t), k_{t+1}(s^t)\}} \left[ \sum_{t=0}^{\infty} \sum_{s^t|s_1} \beta^t \pi(s^t|s_1) u(c_t(s^t)) \right] \right\}$$

subject to the series of state-contingent constraints

$$c_0(s_0) + k_1(s_0) = e^{a_0(s_0)} f(k_0(s_0))$$

$$c_t(s^t) + k_{t+1}(s^t) = e^{a_t(s^t)} f(k_t(s^t)) \quad , \quad \forall t \geq 1, \forall s^t|s_1, s_0$$

## Value function

- Period 0, state  $s_0$  value function:

$$V_0(s_0) = \max_{c_0(s_0), k_1(s_0)} u(c_0(s_0)) \\ + \beta \sum_{s_1|s_0} \pi(s_1|s_0) \left\{ \max_{\{c_t(s^t), k_{t+1}(s^t)\}} \left[ \sum_{s^t|s_1} \sum_{t=0}^{\infty} \beta^t \pi(s^t|s_1) u(c_t(s^t)) \right] \right\}$$

subject to the series of state-contingent constraints

$$c_0(s_0) + k_1(s_0) = e^{a_0(s_0)} f(k_0(s_0))$$

$$c_t(s^t) + k_{t+1}(s^t) = e^{a_t(s^t)} f(k_t(s^t)) \quad , \quad \forall t \geq 1, \forall s^t|s_1$$

The terms in red are exactly  $V_1(s_1)$ .

(Go back and check the definition of  $V_0(s_0)$ ).

# Value function

- Period 0, state  $s_0$  value function:

$$V_0(s_0) = \max_{c_0(s_0), k_1(s_0)} u(c_0(s_0)) + \beta \sum_{s_1|s_0} \pi(s_1|s_0) V_1(s_1)$$

subject to the constraint

$$c_0(s_0) + k_1(s_0) = e^{a_0(s_0)} f(k_0(s_0))$$

- Now we can determine what should be included in  $s$
- We need to know everything such that we can (i) solve the household's decision given  $s_0$ , (ii) fully determine  $s_1$  so that we can solve their problem again tomorrow.

## Value function

- Suppose that we conjecture that the state is  $s_t = (a_t, k_t)$
- Let's try

$$V_0(a_0, k_0) = \max_{c_0, k_1} u(c_0) + \beta \sum_{a_1, k_1 | a_0, k_0} \pi(a_1, k_1 | a_0, k_0) V_1(a_1, k_1)$$

subject to the constraint

$$c_0 + k_1 = e^{a_0} f(k_0)$$

- The  $k_1$  part of  $s_1$  is determined by the choice of capital today  $k_1(a_0, k_0)$
- The  $a_1$  part of  $s_1$  is drawn from the stochastic process for  $a$

$$a' \sim \pi_a(a'|a) \quad \text{i.e.} \quad \text{Prob}[a_1|a_0] = \pi(a_1|a_0)$$

- Therefore the probability of  $(a_1, k_1)$  given  $(a_0, k_0)$  is

$$\pi(a_1, k_1 | a_0, k_0) = \mathbf{1}[k' = k_1(a_0, k_0)] \times \pi_a(a' | a)$$

## Value function

- Conjecture that  $s_t = (a_t, k_t)$

$$V_0(a_0, k_0) = \max_{c_0, k_1} u(c_0) + \beta \sum_{a_1|a_0} \pi_a(a_1|a_0) V_1(a_1, k_1)$$

subject to the constraint

$$c_0 + k_1 = e^{a_0} f(k_0)$$

## Value function

- Conjecture that  $s_t = (a_t, k_t)$

$$V_0(a_0, k_0) = \max_{c_0, k_1} u(c_0) + \beta \sum_{a_1|a_0} \pi_a(a_1|a_0) V_1(a_1, k_1)$$

subject to the constraint

$$c_0 + k_1 = e^{a_0} f(k_0)$$

- In our example, had the following stochastic process:

$$\begin{aligned} a_1 &= \rho a_0 + \varepsilon_1 \quad , \quad \varepsilon_1 \sim N(0, \sigma_\varepsilon) \\ \implies \pi_a(a_1|a_0) &= Prob[a_1|a_0] = \phi\left(\frac{a_1 - \rho a_0}{\sigma_\varepsilon}\right) \end{aligned}$$

where  $\phi(\cdot)$  is the probability under the standard normal distribution

# Value function

- Note that time  $t$  plays no role in the value function
- All of the decisions depend only on the state, not the date  $t$  that decisions happen
- So we can drop time subscripts on  $V_t(a_t, k_t)$  and on variables

$$V(a, k) = \max_{c, k'} u(c) + \beta \sum_{a'|a} \pi_a(a'|a) V(a', k')$$

subject to the constraint

$$c + k = e^a f(k)$$



# Two problems that deliver same solution

## 1. Bellman equation

$$V(a, k) = \max_{c, k'} u(c) + \beta \sum_{a'|a} \pi_a(a'|a) V(a', k')$$

subject to the constraint

$$c + k = e^a f(k) \quad \rightarrow \quad \underbrace{c(a, k), k'(a, k)}_{\text{Policy functions}}$$

## 2. Sequence problem

$$V_0(s_0) := \max_{\{c_t(s^t), k_{t+1}(s^t)\}} \left[ \sum_{t=0}^{\infty} \sum_{s^t|s_0} \beta^t \pi(s^t|s_0) u(c_t(s^t)) \right]$$

subject to the series of state-contingent constraints

$$c_t(s^t) + k_{t+1}(s^t) = e^{a_t(s^t)} f(k_t(s^t)) \quad , \quad \forall t \geq 0, \forall s^t|s_0$$

# Principle of Optimality

- **Result** - Take a plan  $c_t(s^t)$  that solves the sequence problem. Then this sequence must also satisfy the Bellman equation.

*“An **optimal policy** has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision”* - Bellman (1957), “Dynamic Programming”

... if given the state today, you are to make a particular decision, then tomorrow—if the state is the same—you should make the same decision

- **Further result** - This is a *necessary* condition. *“If [**plan**] solves sequence, then [**plan**] solves the Bellman”*. Under additional, easy to verify conditions, the Bellman equation is necessary and sufficient
- **Analogy** - Like sub-game perfection, with an infinite horizon!
- **Analogy** - Makes *perfectly clear* the notion of a ‘sunk cost fallacy’. Past actions only affect decisions today in so far as they are coded into the current period state variables  $s_t$ .

# *Principle of Optimality*

- **Today**, I solve a problem that determines how the state evolves

Given  $(a_t, k_t)$  I choose  $c_t$ , which determines  $k_{t+1}$

- **Tomorrow**, after the resolution of some uncertainty, I am faced with the exact same problem

Given  $(a_{t+1}, k_{t+1})$  I choose  $c_{t+1}$ , which determines  $k_{t+2}$

- The *policy function* (optimal policy) gives the optimal decision in state  $s$

$$c(a, k) \quad k'(a, k)$$

- The *value function* gives the PDV of utility *under the optimal policy*

$$V(a, k) = \sum_{t=0}^{\infty} \sum_{(a_t, k_t) | (a, k)} \beta^t \pi(a_t, k_t) u(c(a_t, k_t))$$

- **Result** - The sequence  $c_t(s^t)$  is generated by a policy function  $c(s)$  (!!!)

## Example 1 - A ‘Cake-eating’ problem

- Sequence problem

$$\max_{\{c_t\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t u(c_t)$$

subject to

$$W_{t+1} = R(W_t - c_t) \quad \forall t \quad , \quad W_0 > 0 \quad , \quad W_{t+1} \geq 0$$

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- Bellman equation

$$V(W) = \max_c u(c) + \beta V(W')$$

subject to

$$W' = R(W - c), \quad W' \geq 0$$

## Example 2 - A job search problem

- An individual begins period  $t$  with an offer of a job at wage  $w$
- She can **accept** the job
  - In which case she works forever at wage  $w_t = w$
- She can **reject** the job
  - In which case she receives unemployment payment  $b$   
and at beginning of  $t + 1$  she draws a new job offer  $w' \sim F(w)$  where  $w' \in [0, \infty)$
  - When working her consumption is  $c_t = w_t$ , when unemployed  $c_t = b$
  - Let  $V(w)$  be the expected PDV of lifetime utility under the optimal policy

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

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- **Result**  $V(w)$  satisfies the Bellman equation

$$V(w) = \max \left\{ \frac{u(w)}{1 - \beta}, \quad u(b) + \int_0^{\infty} V(w') dF(w') \right\}$$

# General problem

## 1. Bellman equation

$$V(x, z) = \max_{x'} F(x, x', z) + \beta \mathbb{E} \left[ V(x', z') \middle| z \right]$$

subject to the constraint

$$x' \in \Gamma(x, z)$$

## 2. Sequence problem

$$V(x_0, z_0) := \max_{\{x_{t+1}\}_{t=0}^{\infty}} \mathbb{E} \left[ \sum_{t=0}^{\infty} \beta^t F(x_t, z_t, x_{t+1}) \right]$$

subject to the sequence of state-contingent constraints

$$x_{t+1} \in \Gamma(x_t, z_t)$$



# General problem

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subject to the constraint

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- Questions
  - If we have  $V$ , how do we find the policy  $x'(x, z)$ ?
  - How do we find  $V$ ?
  - How do we handle *competitive equilibrium* problems?
    - Lucas (1972), Mehra Prescott (1982)

END