

$$\text{Max}_{c_s, \tilde{r}_s, \dots, \tilde{r}_{T-1}} \mathbb{E}_s \left[ \sum_{t=s}^{T-1} \beta^t u(c_t) \mid w_s \right] = \mathbb{E}_s^T(\tilde{c})$$

$$u' > 0, u'' < 0.$$
~~$$w_{t+1} = w_t - c_t + r_t$$~~

risks  
 $\tilde{r}_t$  is  
 i.i.d.

~~$$w_{t+1} = \tilde{r}_t (w_t - c_t) \quad w_s \text{ given.}$$~~

independent (identically) distributed.  
 Know  $w_t$  at time  $t$ , but not before.  
 ( $w_t$  depends on  $\dots, r_{t-2}, r_{t-1}$ ).

Terminal condition  $w_T \geq 0$ .

~~$$\beta_s u(c_s) + \mathbb{E}_s \left[ \beta_{s+1} u(c_{s+1}(w_{s+1})) + \mathbb{E}_{s+1} [\beta_{s+2} \dots] \right]$$~~

Remember  $\mathbb{E}_s \mathbb{E}_{s+1} = \mathbb{E}_s$ .  
 iterated expectations

~~$$\mathbb{E}_s \mathbb{E}_{s+1} g = \int_{\Omega_s} g$$

$$\mathbb{E}_s \mathbb{E}_{s+1} g(w_s, w_{s+1})$$

$$= \int_{\Omega_s \times \Omega_{s+1}} g(w_s, w_{s+1}) f(w_s, w_{s+1}) dw_s dw_{s+1}$$

$$= \int_{\Omega_s} f_s(w_s) \int_{\Omega_{s+1}} (\mathbb{E}_{s+1} g(w_s, w_{s+1})) dw_{s+1} dw_s$$~~

$$\mathbb{E}_s g(\omega_s, \omega_{s+1})$$

(2)

$$= \mathbb{E}_s \left[ \mathbb{E}_{s+1} \left[ g(\omega_s, \omega_{s+1}) \mid \omega_s \right] \right]$$

$$\text{Max } \mathbb{E}_s \sum_{t=s}^T \beta_t u(c_t)$$

$\omega_s$  fixed,

$\omega_{T+1} \geq 0$ .

$$\text{ST } \omega_{t+1} = \tilde{r}_t (\omega_t - c_t),$$

~~Work backwards~~ Work backwards.

max value  
state function

In period  $T$ , (when  $s=T$ ),

$$c_T = \omega_T, \quad V_T(\omega_T) = \beta_T u(\omega_T).$$

In period  $T-1$ ,  $s=T-1$ ,

$$\text{max}_{c_{T-1}} \left\{ \beta_{T-1} u(c_{T-1}) + \mathbb{E} V_T(\omega_T) \right\}$$

↑  
period  
 $T-1$ .

Result of an optimal  
policy in period  $T$ .

$$\omega_T = \tilde{r}_{T-1} (\omega_{T-1} - c_{T-1})$$

↑  
random  
gross return

↑  
savings

$$\max_{c_{T-1}} \beta_{T-1} u(c_{T-1}) + \mathbb{E} \beta_T u(\tilde{r}_{T-1} (w_{T-1} - c_{T-1}))$$

$$c_{T-1} \leq w_{T-1}$$

$$0 = \beta_{T-1} u'(c_{T-1}) - \mathbb{E} \beta_T u'(\tilde{r}_{T-1} (w_{T-1} - c_{T-1})) \tilde{r}_{T-1}$$

$$u'(c_{T-1}) = \mathbb{E} \beta_T \tilde{r}_{T-1} u'(\tilde{r}_{T-1} (w_{T-1} - c_{T-1}))$$

$$1 = \beta_T / \beta_{T-1} \mathbb{E} \tilde{r}_{T-1} \left[ \frac{u'(\tilde{r}_{T-1} (w_{T-1} - c_{T-1}))}{u'(c_{T-1})} \right]$$

Stochastic Euler equation.

$$u(c) = \frac{c^{1-\epsilon}}{1-\epsilon}, \quad \epsilon \text{ risk and frustration aversion } (\epsilon \geq 0)$$

$$u'(c) = c^{-\epsilon} \quad (\text{even if } \epsilon = 1)$$

$$c_{T-1}^{-\epsilon} = \frac{\beta_T \mathbb{E} \tilde{r}_{T-1} \left[ \tilde{r}_{T-1} (w_{T-1} - c_{T-1}) \right]}{\beta_{T-1}}$$

$$= \frac{\beta_T}{\beta_{T-1}} (w_{T-1} - c_{T-1})^{-\epsilon} \mathbb{E} \tilde{r}_{T-1}^{1-\epsilon}$$

$$c_{T-1} = \left( \frac{\beta_T}{\beta_{T-1}} \right)^{\frac{1}{\epsilon}} (w_{T-1} - c_{T-1}) \left( \mathbb{E} \tilde{r}_{T-1}^{1-\epsilon} \right)^{\frac{1}{\epsilon}}$$

$$c_{T-1} = \gamma_{T-1} w_{T-1}, \quad w_T = \tilde{r}_{T-1} (1 - \gamma_{T-1}) w_{T-1}$$

- incl. of  $w_{T-1}$

5

$$\cancel{\gamma_{T-1}} = \cancel{\frac{C_{T-1}}{W_{T-1}}}$$

$$\gamma_{T-1} = \left( \frac{\beta_T}{\beta_{T-1}} \right)^{3/1-\varepsilon} (1-\gamma_{T-1}) \left( \frac{E_{T-1}}{E_{T-1}} \right)^{1-\varepsilon} \left( \frac{r_{T-1}}{r_{T-1}} \right)^{1-\varepsilon}$$

With  $u(c) = \frac{c^{1-\epsilon}}{1-\epsilon}$  ( $\epsilon > 0$ )

$$V_s(w_s) = \max \mathbb{E}_s \left[ \sum_{t=s}^T \beta_t u(c_t) / w_s \right]$$

STATE VALUATION FUNCTION.

with  $w_s$  given.

$$= \frac{\alpha_s w_s^{1-\epsilon}}{1-\epsilon}$$

s.t.  $w_{t+1} \geq 0$   
 $c_t = \gamma_t w_t$   
 $\alpha_s, \gamma_s > 0$ .  
Constants (depend on probs?).

Induction hypothesis.

BELLMAN equation (finite horizon).

True for general  $u$ .

$$V_s(w_s) = \max_{c_s} \left\{ \beta_s u_s(c_s) + \mathbb{E}_{s+1} \left[ V_{s+1}(w_{s+1}) \right] \right\}$$
  
 $c_s(w_s) = \arg$

PRINCIPLE OF OPTIMALITY

BACKWARD.

PROVE BY INDUCTION

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

that  $V_s(w_s) = \frac{\alpha_s w_s^{1-\epsilon}}{1-\epsilon}$ ,  $c_s(w_s) = \gamma_s w_s$

PROOF. When  $s \neq T$ ,  $\gamma_T \geq 1$ ,

$$\alpha_T = \beta_T$$

Induction hypothesis: Suppose true for  $s+1$ .

$$V_s(w_s) = \max_{\gamma_s} \left\{ \beta_s \frac{(\gamma_s w_s)^{1-\varepsilon}}{1-\varepsilon} + \mathbb{E}_s \frac{\alpha_{s+1} \left[ \tilde{r}_s (1-\gamma_s) w_s \right]^{1-\varepsilon}}{1-\varepsilon} \right\}$$

$$c_s(w_s) = \arg$$

~~$$V_s(w_s) = \max_{\gamma_s} \left\{ \beta_s \frac{(\gamma_s w_s)^{1-\varepsilon}}{1-\varepsilon} + \mathbb{E}_s \frac{\alpha_{s+1} \left[ \tilde{r}_s (1-\gamma_s) w_s \right]^{1-\varepsilon}}{1-\varepsilon} \right\}$$

$$c_s(w_s) = \arg$$~~

$$V_s(w_s) = \max_{\gamma_s} \left\{ \beta_s \gamma_s^{1-\varepsilon} + \mathbb{E}_s \frac{\alpha_{s+1} \left[ \tilde{r}_s (1-\gamma_s) \right]^{1-\varepsilon}}{1-\varepsilon} \right\}$$

$$c_s(w_s) = \arg$$

maximand  $\frac{\beta_s \gamma_s^{1-\varepsilon}}{1-\varepsilon} + \frac{\alpha_{s+1} (1-\gamma_s)^{1-\varepsilon} \mathbb{E}_s \tilde{r}_s^{1-\varepsilon}}{1-\varepsilon}$

(when returns are

serially independent).

FOC:  $\beta_s \gamma_s^{-\varepsilon} - \alpha_{s+1} (1-\gamma_s)^{-\varepsilon} \mathbb{E}_s \tilde{r}_s^{1-\varepsilon} = 0$

$$\beta_s^{-1/\varepsilon} \gamma_s = \alpha_{s+1}^{1/\varepsilon} (1-\gamma_s) \mathbb{E}_s \tilde{r}_s^{1-\varepsilon}$$

$$0 < \gamma_s = \frac{\alpha_{s+1}^{-1/\varepsilon} \mathbb{E}_s \tilde{r}_s^{1-\varepsilon}}{\beta_s^{-1/\varepsilon} + \alpha_{s+1}^{-1/\varepsilon} \mathbb{E}_s \tilde{r}_s^{1-\varepsilon}}$$

$$J = \left( \mathbb{E}_s \tilde{r}_s^{1-\varepsilon} \right)^{-1/\varepsilon} < 1$$

$\alpha_s = \dots$  EXERCISE.

state control

$$\text{Max } \mathbb{E} \left\{ \sum_{s=0}^{T-1} u_s(x_s, y_s) + \phi_T(x_T) \right\}$$

\$x\_s\$ given

LAW OF MOTION:  $x_{t+1} = \xi_t(x_t, y_t, \epsilon_t)$

Conditionally independent random shocks given  $x_t, y_t$

Controlled Markov process.

$$V_s(x_s) = \max_{y_s \in F_s(x_s)} \left\{ \dots \right\}$$

strategy

maximand

$$= u_s(x_s, y_s) + \mathbb{E}_s [V_{s+1}(x_{s+1}) | x_s, y_s]$$

immediate return

Principle of optimality in dynamic programming

Bellman equation

"one-shot deviation principle" in games

If any deviation improves, there exists a one-shot deviation that improves.

(9)

$$\max \sum_{t=s}^{\infty} \beta^{t-s} u(c_t), \quad w_s \text{ given}$$

$0 < \beta < 1$ .

$$w_{t+1} = \tilde{r}_t (w_t - c_t) \quad u' > 0, u'' < 0.$$

IID random variables.  
 Constant discount factor  $\beta$ ;  $u$  independent of  $\epsilon$ .  
 STATIONARY (infinite horizon)  
 DYNAMIC PROGRAM.

lim of  ~~$\beta^t w_t$~~  exists and is  $\geq 0$ .

$w_t \geq 0$  for all time. (\*)

"OBVIOUSLY" (?),

$$V_s(w) = V_{s'}(w) \text{ for all } s, s'$$

$\uparrow$  max value function.  $J_s$ .

$$V(w) = \max_c \{ u(c) + \beta \mathbb{E} V(\tilde{r}(w-c)) \}$$

$\uparrow$  next period's uncertain wealth

$c(w) = \text{arg}$

$V$  appears on both left and right hand sides.  
 Fixed point in function space.



# General stationary problem

$$\max_u \mathbb{E}_s \sum_{t=s}^{\infty} \beta^{t-s} f(x_t, u_t)$$

s.t.  $u_t \in F(x_t)$   $(t=s, s+1, \dots)$   $(0 < \beta < 1)$

$P(x_{t+1} | x_t, u_t)$  — ind. of  $t$ .

Time-invariance constraint.

Bellman equation.

$$V(x) = \max_{u \in F(x)} \{ f(x, u) + \beta \mathbb{E}[V(x') | x, u] \}$$

$$u^*(x) = \arg \max_{u \in F(x)} \{ f(x, u) + \beta \mathbb{E}[V(x') | x, u] \}$$

Find  $V, u^*$  to solve Bellman equation.

Will be sol<sup>n</sup> if  $f$  is BOUNDED.

Otherwise:

Check that  $V$  is the value of choosing  $u^*(x)$ .

$$u(c) = \frac{c^{1-\epsilon}}{1-\epsilon} \quad (\epsilon > 0; \text{ist})$$

luc y = 1

$$V_s(\omega_s) = \frac{\alpha \omega_s^{1-\epsilon}}{1-\epsilon} \quad \left. \vphantom{V_s(\omega_s)} \right\} \text{finite horizon.}$$

$$c_s(\omega_s) = \gamma_s \omega_s$$

As  $T \rightarrow \infty$ ,  
 $c_s^T(\omega_s) \rightarrow \gamma \omega_s$   
 $V_s^T(\omega_s) \rightarrow \frac{\alpha \omega_s^{1-\epsilon}}{1-\epsilon}$

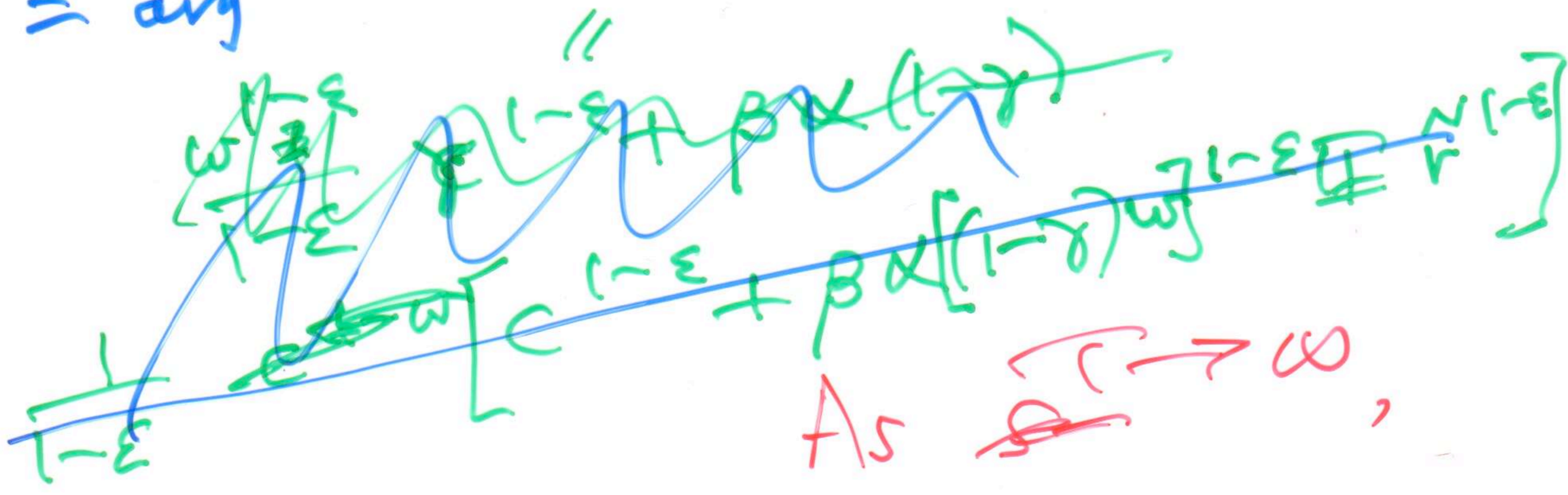
CONJECTURE

When  $T = \infty$ ,

$$V(\omega) = \frac{\alpha \omega^{1-\epsilon}}{1-\epsilon}, \quad c(\omega) = \gamma \omega$$

$$\frac{\alpha \omega^{1-\epsilon}}{1-\epsilon} = \left\{ \max_c \frac{c^{1-\epsilon}}{1-\epsilon} + \beta \mathbb{E} \alpha \left[ \frac{V(\omega - c)}{1-\epsilon} \right] \right\}$$

arg =  $\omega$   
arg =  $\omega$



As  $T \rightarrow \infty$ ,

$$\frac{\alpha}{1-\epsilon} = \left\{ \max_{\gamma} \gamma \right\}$$

arg =  $\omega$

$$c_s^T(\omega_s) = \gamma_{T-s} \omega_s$$

$\rightarrow \gamma \omega_s$  as  $T \rightarrow \infty$

$$V_s^T(\omega_s) = \frac{\alpha \omega_s^{1-\epsilon}}{1-\epsilon}$$

(12)  $\frac{\alpha}{1-\varepsilon} = \max_{\gamma} \frac{\gamma^{1-\varepsilon}}{1-\varepsilon} + \beta \frac{E[\alpha(1-\gamma)\tilde{r}]}{1-\varepsilon}$

$= \max_{\gamma} \frac{\gamma^{1-\varepsilon}}{1-\varepsilon} + \frac{\beta E[\alpha(1-\gamma)]}{1-\varepsilon} E\tilde{r}^{1-\varepsilon}$

FOC  $\gamma^{-\varepsilon} = \beta \alpha^{1-\varepsilon} (1-\gamma)^{-\varepsilon} E\tilde{r}^{1-\varepsilon}$

Solve to find  $\gamma$ , as a function of  $\alpha, \beta, E\tilde{r}^{1-\varepsilon}$   
 Substitute to find  $\alpha$ .

Candidate optimal policy.

$\gamma = (\beta \alpha^{1-\varepsilon})^{-\frac{1}{\varepsilon}} (1-\gamma) (E\tilde{r}^{1-\varepsilon})^{-1/\varepsilon}$

Substitute to find  $\alpha$ .

Suppose that  $f(x, u)$  is bounded both above and below.  
 $M_1 \leq f(x, u) \leq M_2$  for all  $x, u$ .

Bellman eq.

$$V(x) = \max_{u \in F(x)} \{ f(x, u) + \beta \mathbb{E}[V(\tilde{x}) | x, u] \}$$
$$u^*(x) = \arg$$

$$0 < \beta < 1.$$

THEOREM

Under this boundedness condition, the Bellman eq. has a unique sol<sup>n</sup>.

$V(x)$  for each  $x$ , and any optimizing  $u^*(x)$  is an optimal policy.

Sketch of Proof.

Given any function  $\frac{M_1}{1-\beta} \leq V(x) \leq \frac{M_2}{1-\beta}$

$V(x)$  satisfying  $\frac{M_1}{1-\beta} \leq V(x) \leq \frac{M_2}{1-\beta}$  for all  $x$ ,

$$\sum_{t=0}^{\infty} \beta^t f(x_t, u_t) \in \left[ \frac{M_1}{1-\beta}, \frac{M_2}{1-\beta} \right]$$

Define  $(T^u V)(x) = f(x, u) + \beta \mathbb{E}[V(\tilde{x}) | x, u]$

and  $(T^* V)(x) = \max_{u \in F(x)} (T^u V)(x).$

Prove that

~~$(T^*V_1)$~~

Define  $d(V_1, V_2) = \sup_{x \in X} |V_1(x) - V_2(x)|$

[Finite because  $V_1, V_2$  are bounded].

Prove that  $d(T^*V_1, T^*V_2) \leq \beta d(V_1, V_2)$ .

Contraction mapping.

Bellman has a unique solution

$V = T^*V = T^{u^*}V$

$u^*$  - optimal policy.

\* This will be an optimum

(needs checking?)

# EXAMPLES OF DANGER!!

AI

PP. 461-2, Counterexamples.

Example 2.  $0 < \beta < 1$ .

$$\text{Max } \sum_{t=0}^{\infty} \beta^t (1 - u_t), \quad u_t \in [0, 1]$$

$$\text{ST } x_{t+1} = \frac{1}{\beta} (x_t + u_t), \quad x_0 > 0.$$

$$\left( \geq \frac{1}{\beta} x_t \rightarrow \infty \right).$$

Objective  $f(x, u) = 1 - u \in [0, 1]$   
is bounded.

Bellman equation:

$$J(x) = \max_u \left\{ 1 - u + \beta J\left(\frac{1}{\beta}(x+u)\right) \right\}$$

$$u^*(x) = \arg \max_u$$

Look for solution with  $J(x) = \gamma + x$ .

$$\gamma + x = \max_u \left\{ 1 - u + \beta \left[ \frac{1}{\beta}(x+u) + \gamma \right] \right\}$$

$$= \max_u \{ 1 + x + \beta \gamma \}$$

$$u^*(x) \text{ arbitrary in } [0, 1] \quad \gamma = 1 + \beta \gamma, \quad \gamma = \frac{1}{1-\beta}.$$

[UNBOUNDED]

EVEN IF  $f$  IS BOUNDED. (A2)

~~the~~ solution to the Bellman equation could be inappropriate (if it is UNBOUNDED).

WHAT WE NEED:

A solution  $J(x), u^*(x)$  to the Bellman equation for which  $J$  is the value of following the policy  $u^*$ .

In our example,

max  $\sum_{t=0}^{\infty} \beta^t (1-u_t)$  s.t.  $u_t \in [0, 1]$ .

Solution: choose  $u^* = 0$  all  $t$ .

Then ~~J~~  $J^{u^*}(x) = \sum_{t=0}^{\infty} \beta^t = \frac{1}{1-\beta}$

---

This is an alternative sol<sup>n</sup> to the Bellman equation: (BOUNDED?)

# BELLMAN

(A3)

$$J(x) = \max \left\{ 1 - u + \beta J\left(\frac{x+u}{\beta}\right) \right\}$$
$$u^*(x) = \arg$$

TRY  $J(x) = \text{constant (ind. of } x),$   
(c)

$$c = \max \left\{ 1 - u + \beta \frac{c}{\beta} \right\}$$
$$u^*(x) = \arg$$

$$u^* = 0, \quad c = 1 + \beta c, \quad c = \frac{1}{1-\beta}.$$

~~$\beta c = \beta + c$~~

If return function is bounded,  
there is a UNIQUE BOUNDED  
solution to the Bellman equation,  
which is the right one.

$$[0 < \beta < 1]$$



ATC

# EXAMPLES of economically interesting unbounded utility functions.

$$u(c) = \begin{cases} \frac{c^{1-\varepsilon}}{1-\varepsilon} & \text{bounded below, not above, iff } 0 \leq \varepsilon < 1. \\ \ln c \text{ (if } \varepsilon = 1) & \text{bounded above, not below, iff } 1 < \varepsilon < \infty. \\ c^{-\varepsilon} & \text{unbounded both above and below.} \end{cases}$$

$$u(c) = -e^{-\alpha c} \quad (\alpha \geq 0)$$

bounded above; bounded below if we impose  $c \geq 0$ .

$$u(c) = -\frac{1}{2}(c - c^*)^2 \quad (c^* \geq 0)$$

DITTO  
if  $0 \leq c \leq c^*$ .

~~RANGE,~~

~~AS~~  
AS.

LOWER BOUND CASE.

Suppose  $f(x, u) \geq \gamma$   
for all  $x, u$ .  
(where  $\gamma = 0$  if  $\beta = 1$ ).

A solution to the Bellman equation which equals the true value of the corresponding optimal policy will be optimal.

UPPER BOUND CASE.

(A6)

$$f(x, u) \leq \gamma \quad (\text{all } x, u).$$

1) Find a solution to the Bellman equation which is also bounded above (by  $\frac{\gamma}{1-\beta}$ ).

(necessary condition for it to be the value of a feasible policy?).

2) Check that either:

(a) It is the unique solution that is bounded above by  $\frac{\gamma}{1-\beta}$ .

OR (b) It is the limit as  $T \rightarrow \infty$  of  $T$ -horizon values (and policies).

AT

P. 462, Example 3.

$$\text{Max } \sum_{t=0}^{\infty} \beta^t x_t (u_t - \alpha)$$

$$\text{ST } u_t \in [0, \alpha] = U.$$

$$\alpha\beta = 1. \quad x_{t+1} = x_t u_t, \quad x_0 > 0 \text{ given.}$$

$$0 < \beta \leq 1, \quad \alpha > 0.$$

Objective bounded above by 0,  
but unbounded below.

Bellman equation:

$$J(x) = \max_{u \in U} \{ x(u - \alpha) + \beta J(xu) \}$$

$$u^*(x) = \arg \max_{u \in U} \{ x(u - \alpha) + \beta J(xu) \}$$

Look for solution  $J(x) = \gamma x$ .

$$\gamma x = \max_{u \in U} \{ x(u - \alpha) + \beta \gamma x u \}$$

$$= \max_{u \in U} \{ x u (1 + \beta \gamma) - \alpha x \}.$$

$$u^*(x) = \alpha, \quad (\geq 0).$$

$$\gamma = \alpha \beta \gamma = \gamma, \quad \text{Solution for all } \gamma \geq 0.$$

A8

Check that  $J$  is the actual value of the policy.

Choose  $u = \text{constant}$ .

$$x_{t+1} = x_t u$$

$$\cancel{x_0}$$
$$x_t = x_0 u^t.$$

$$\sum_{t=0}^{\infty} \beta^t x_t (u - \alpha)$$

$$= \sum_{t=0}^{\infty} x_0 (\beta u)^t (u - \alpha)$$

$$= \frac{x_0 (u - \alpha)}{1 - \beta u} \quad (\text{if } \beta u < 1, \text{ or } u < \alpha).$$

A9

# PROCEDURES for solving Bellman equation:

- 1) Finite horizon, then take limits. (guess?)
- 2) Read KLJUDD -
- 3) POLICY IMPROVEMENT.

P.458, (17). § 12.7.

$$\text{Max}_u \mathbb{E} \left[ \sum_{t=0}^{\infty} \beta^t f(x, u) \right]$$

$$x_{t+1} = g(x_t, u_t, v_{t+1})$$

random shocks.

$P(v_{t+1} | v_t)$  specified.

$u \in U$ ,  $x_0$  given.

$$J(x, v), \quad u^*(x, v)$$

A10

$$J(x, v) = \max_{u \in U} \{ f(x, u) + \beta \mathbb{E} [J(x', v') | x, v] \}$$

$$x' = g(x, u, v'), \quad P(v' | v)$$

$$(T^u J)^{(x, v)} = f(x, u) + \beta \mathbb{E} [J(x', v') | x, u, v]$$

$$(T^* J)(x, v) = \max_{u \in U} (T^u J)(x, v)$$

Bellman equation  $J = T^* J = T^u J$

### POLICY IMPROVEMENT.

Start with arbitrary  $u_0(x, v), (x \in \mathcal{X}, v \in \mathcal{V})$

Find its value, which satisfies

$$J_0 = J^{u_0} = T^{u_0} J_0$$

$$T^* J_0 = T^{u_1} J_0$$

$$J_1 = J^{u_1} = T^{u_1} J_1$$

$$T^* J_{k-1} = T^{u_k} J_{k-1}$$

$$J_k = J^{u_k} = T^{u_k} J_k$$