

One more problem set: short.

Hyperbolic Discounting

Phelps/Pollak (68)

Rabson (97)

- infinite horizon: $t=0,1,\dots$
- one individual who lives forever
 - sequence of different "selves"
 - self t has preferences: $u(c_t) + \beta \sum_{j=1}^{\infty} \delta^j u(c_{t+j})$, $\beta, \delta \in (0,1]$
 - $\beta=1 \Rightarrow$ exponential (standard) discounting
 - $\beta < 1 \Rightarrow$ quasi-hyperbolic discounting
- savings technology $f(k_t)$ (e.g. $f(k_t) = R k_t$)
 - $c_t + k_{t+1} \leq f(k_t)$
 - k_0 given
- "First best" - self 0 decides on all c_t .
 - From period 1 on, solves: $\max \sum_{t=1}^{\infty} \delta^{t-1} u(c_t)$
 - s.t. $c_t + k_{t+1} \leq f(k_t) \quad \forall t$
 k_1
 - Value function: $W(k) = \max_c \{ u(c) + \delta W(f(k) - c) \}$
 - $\Rightarrow W(k) \searrow \frac{c(k)}{\text{policy fcn}}$
 - Period 0: $V(k_0) = \max_{c_0} \{ u(c_0) + \beta \delta W(f(k_0) - c_0) \}$
 - $\Rightarrow V(k_0), \tilde{c}(k_0)$
- "No commitment" - self t decides on c_t .
 - noncooperative game
 - Focus on Markov equilibrium, symmetric
 - $c_t(k_t) = c(k_t)$ (action depends only on state)

• compute Markov equilibrium

• For any $c(k)$, define: $W(k_t) \equiv \sum_{j=0}^{\infty} \delta^j u(c(k_{t+j}))$

• $k_{t+j+1} = f(k_{t+j}) - c(k_{t+j})$

• i.e. taking as given that all future selves play the Markov strategy

• Taking $c^*(k)$ as given, self 0 solves

$$V(k_0) = \max_c \{ u(c) + \beta \delta W(k_1) \}$$

$$\text{s.t. } k_1 = f(k_0) - c$$

$$W(k_1) = \sum_{j=0}^{\infty} \delta^j u(c^*(k_{1+j}))$$

$\Rightarrow c^*(k_0)$ (symmetric equilibrium strategy)

$$\Rightarrow V(k_0) = u(c^*(k_0)) + \beta \delta \sum_{j=0}^{\infty} \delta^j u(c^*(k_{1+j}))$$

$$\begin{aligned} \Rightarrow V(k_0) - (1-\beta)u(c^*(k_0)) &= \beta u(c^*(k_0)) + \beta \delta \sum_{j=0}^{\infty} \delta^j u(c^*(k_{1+j})) \\ &= \beta W(k_0) \end{aligned}$$

$$\Rightarrow \beta W(k) = \max_c \{ u(c) + \beta \delta W(f(k) - c) \} - (1-\beta)u(c^*(k))$$

Steps:

• start with $c^*(k)$ that solves (for a guessed $W(k)$)

$$\bullet TW(k) = \frac{1}{\beta} \max_c \{ u(c) + \beta \delta W(f(k) - c) \} - \left(\frac{1-\beta}{\beta} \right) u(c^*(k))$$

\Rightarrow Fixed point: $w = Tw$

\Rightarrow The associated $c^*(k)$ is a symmetric Markov equilibrium of this game.

Example

Assume $\circ u(c) = \log(c)$

$\circ f(k) = Ak^\alpha$ (ie if $\alpha=1$, $R=A$)

Guess: $W(k) = a \log k + b$

$$\beta T W(k) = \max_c \{ \log(c + a\beta\delta \log(Ak^\alpha - c) + \beta\delta b) - (1-\beta) \log(c^*(k)) \}$$

$$\text{FOC: } \frac{1}{c} = \frac{\alpha\beta\delta}{Ak^\alpha - c} \Rightarrow c = \frac{1}{1+\alpha\beta\delta} Ak^\alpha \xrightarrow{\text{symmetry}} c^* = \frac{1}{1+\alpha\beta\delta} Ak^\alpha$$

$$\Rightarrow \beta(a \log k + b) = \log\left(\frac{Ak^\alpha}{1+\alpha\beta\delta}\right) + \alpha\beta\delta \log\left(\frac{\alpha\beta\delta}{1+\alpha\beta\delta} Ak^\alpha\right) + \beta\delta b - (1-\beta) \log\left(\frac{1}{1+\alpha\beta\delta} Ak^\alpha\right)$$

Solving for a, b , we get: (we don't really care about b)

$$\beta a = \alpha(1+\alpha\beta\delta - (1-\beta)) \Rightarrow \beta a - \alpha\beta\delta a = \alpha\beta \Rightarrow a = \frac{\alpha}{1-\alpha\delta}$$

$$\Rightarrow c^*(k) = \frac{1-\alpha\delta}{1-\alpha\delta(1-\beta)} Ak^\alpha$$

save less than when $\beta=1$
(exponential discounters)

Dynamic Adverse Selection (Recursive Contracts) Atkeson-Lucas

- \circ micro-founding the lack of complete insurance
- \circ risk averse agent subject to taste shocks (unobservable)

$\theta_t u(c_t)$

(θ_t - privately known)

- \circ risk-neutral principal who provides consumption that may vary

$\circ u(c) = \ln c, E[\theta] = 1$

history of taste shocks

FB: $\max_{c_t(\theta^t)}$

$$\sum_{t, \theta^t} \beta^t \theta_t u(c_t(\theta^t)) \Pr[\theta^t]$$

$$\text{s.t. } \sum_{t, \theta^t} q^t c_t(\theta^t) \Pr[\theta^t] \leq R \quad (\lambda)$$

FOC: assuming $(\beta=q)$ $\theta_t u'(c_t(\theta^t)) = \lambda$

• c_t is just a fun of θ_t , not of θ^{t-1}

Second Best:

$$K(w_0) = \min \sum_{t, \theta^t} q^t c(u_t(\theta^t)) \Pr[\theta^t] \quad , \quad c(u) = \exp\{-u\}$$

$$\text{s.t. } w_0 = \sum_{t, \theta^t} \beta^t \theta_t u_t(\theta^t) \Pr[\theta^t] \quad (\text{Promise-Keeping})$$

$$\sum_{t, \theta^t} \beta^t \theta_t u_t(\theta^t) \Pr[\theta^t] \geq \sum_{t, \theta^t} \beta^t \theta_t u_t(\widehat{\Delta^t}(\theta^t)) \Pr[\theta^t] \quad (\text{IC})$$

reporting fun

$$\text{where } \Delta^t: \underbrace{\theta \times \dots \times \theta}_{t+1 \text{ times}} \rightarrow \underbrace{\theta \times \dots \times \theta}_{t+1 \text{ times}} \quad \forall \Delta^t$$

$$\text{induces: } \Delta_t: \theta^{t+1} \rightarrow \theta$$

$$\text{• truth-telling: } \Delta^{t*}(\theta^t) = \theta^t, \quad \Delta_t^*(\theta^t) = \theta_t$$

Assume iid shocks: $\Pr[\theta^t] = \pi(\theta_t) \pi(\theta_{t-1}) \dots \pi(\theta_0)$

• continuation utility

$$\text{• } w_t(\theta^{t-1}) = \sum_{s, \theta^{t+s}} \beta^s \theta_s u_{t+s}(\theta^{t+s}) \Pr[\theta^s]$$

must coincide with θ^{t-1} for first $t-1$ periods.

$$\text{(PK)} \Rightarrow w_t(\theta^{t-1}) = \sum_{\theta^t} [\theta_t u_t(\theta^{t-1}, \theta_t) + \beta w_{t+1}(\theta^{t-1}, \theta_t)] \pi(\theta_t) \quad \forall t, \theta^{t-1}$$

using one-shot deviation principle

$$\text{(IC)} \Rightarrow \theta_t u_t(\theta^{t-1}, \theta_t) + \beta w_{t+1}(\theta^{t-1}, \theta_t) \geq \theta_t u_t(\theta^{t-1}, \hat{\theta}_t) + \beta w_{t+1}(\theta^{t-1}, \hat{\theta}_t) \quad \forall \hat{\theta}_t \in \theta, \forall t, \forall \theta^{t-1}$$

Recursive problem: ($\gamma = \beta$)

$$K(w) = \min_{u(\theta), w'(\theta)} \sum_{\theta} [c(u(\theta)) + \beta K(w'(\theta))] \pi(\theta)$$

$$\text{s.t. } w = \sum_{\theta} [\theta u(\theta) + \beta w'(\theta)] \pi(\theta) \quad (\text{PK})$$

$$\theta u(\theta) + \beta w'(\theta) \geq \theta u(\theta') + \beta w'(\theta') \quad \forall \theta, \theta' \quad (\text{IC})$$

will get $\left. \begin{matrix} u(w, \theta) \\ w'(w, \theta) \end{matrix} \right\}$ policy functions

Recall that $u(c) = \ln c$
 Suppose $w_0 = 0$. Get $u_t^*(\theta^t)$

Claim: $w_0 \neq 0 \Rightarrow$ get $\tilde{u}_t(\theta^t) = u_t^*(\theta^t) + (1-\beta)w_0$ optimal $\forall t, \theta^t$

$$\begin{aligned} \text{Then } K(w_0) &\cong \sum_{t, \theta^t} \beta^t \exp\{u_t^*(\theta^t) + (1-\beta)w_0\} \Pr[\theta^t] \\ &= \exp\{(1-\beta)w_0\} \underbrace{\sum_{t, \theta^t} \beta^t \exp\{u_t^*(\theta^t)\} \Pr[\theta^t]}_{=A} \end{aligned}$$

$$\Rightarrow K(w_0) = A \exp\{(1-\beta)w_0\}$$

Also, know:

$$g^u(\theta, w) = (1-\beta)w + h^u(\theta) \rightarrow \text{random walk}$$

$$g^{w'}(\theta, w) = w + h^{w'}(\theta) \rightarrow \text{random walk}$$

↑ iid shocks

$$c = \exp\{u\} \rightarrow \text{geometric random walk}$$

$$\begin{aligned} &\Rightarrow w_t(w_0, \theta^t) \\ &= w_0 + \sum_{s=0}^{t-1} h^{w'}(\theta_s) + h^{w'}(\theta_t) \\ &\Rightarrow u_t(w_0, \theta^t) \\ &= (1-\beta)w_0 + (1-\beta) \sum_{s=0}^{t-1} h^u(\theta_s) \\ &\quad + (1-\beta)h^u(\theta_t) + h^u(\theta_t) \end{aligned}$$

$$\begin{aligned} \text{Var}(u_t(w_0, \theta^t)) &= \text{Var}[(1-\beta)w_0 \\ &\quad + (1-\beta) \sum_{s=0}^{t-1} h^u(\theta_s) + h^u(\theta_t)] \rightarrow +\infty \text{ as } t \rightarrow \infty \end{aligned}$$

$\mathbb{E}_t[c_{t+1}] = c_t \Rightarrow c_t \rightarrow 0$ a.s. "Immiseration result"
 Martingale convergence thm