

1 Lecture 9: overview

- discussion: monitoring
deterministic vs. random
- moral hazard: optimal UI
- lack of commitment:
 - one sided / partial equilibrium
 - two sided / GE (2 agent/2 shock case)

2 optimal UI

- Utility:

$$U = E \sum_{t=0}^{\infty} \beta^t [u(c_t) - a_t]$$

- a = effort
- $p(a)$ = prob of finding a job
- $c_t = w$ if employed $c_t = \tau_t$ otherwise
- "planner" is risk neutral and evaluates cost

$$C \equiv E \sum_{t=0}^{\infty} \beta^t \tau_t$$

- Pareto Problem: frontier between C and U :
 $\min C$ s.t. $U \geq V$
or $\max V$ s.t. $C \leq \bar{C}$

2.1 First Best: Effort observable

- sequence: tedious notation but possible

- recursive:

$$C(V) = \min \{c + \beta(1 - p(a))C(V^u)\}$$

$$V = u(c) - a + \beta(1 - p(a))V^u + \beta p(a)V^e$$

- focs:

$$1 - \theta = 0$$

$$\beta(1 - p(a))C'(V^u) - \theta\beta(1 - p(a)) = 0$$

$$-\beta p'(a)C(V^u) + \theta\beta p'(a)V^u - \theta\beta p'(a)V^e + \theta = 0$$

- simplifying

$$\theta = \frac{1}{u'(c)}$$

$$C'(V^u) = \theta$$

$$C(V^u) = \left[V^u - V^e + \frac{1}{\beta p'(a)} \right] \theta$$

- result: V_t^u is constant $\Rightarrow c_t^u$ is constant

2.2 Second Best: Effort Unobservable

- sequence problem is not very tractable (Shavell and Weiss perform a variational argument for their results)
- recursive formulation

$$C(V) = \min \{c + \beta(1 - p(a))C(V^u)\}$$

$$V = u(c) - a + \beta(1 - p(a))V^u + \beta p(a)V^e$$

$$\beta p'(a)[V^e - V^u] = 1$$

- focs

$$1 - \theta u'(c) = 0$$

$$\beta(1 - p(a))C'(V^u) - \theta\beta(1 - p(a)) + \eta\beta p'(a) = 0$$

$$-\beta p'(a)C(V^u) + \underbrace{\theta\beta p'(a)V^u - \theta\beta p'(a)V^e + \theta}_{=0 \text{ from agent's foc}} + \eta\beta p''(a)[V^e - V^u] = 0$$

- simplifying:

$$\theta = \frac{1}{u'(c)}$$

$$C'(V^u) = \theta - \eta \frac{p'(a)}{1 - p'(a)}$$

envelope condition implies

$$C'(V) = \theta$$

- results:
 V_t^u is decreasing
 \Rightarrow (using envelope and f.o.c. w.r.t. c) c_t^u decreasing

Remarks:

- relaxing $c_t^e = w$ (Hopenhayn and Nicolini, 1997)
- agents save/borrow
- welfare gains of optimal program

3 Lack of commitment: One Sided / Partial Equilibrium

Source: LS Chapter 15 section 401-409

$$P(w) = \min \sum_{s \in S} \pi_s [c_s - y_s + \beta P(w'_s)]$$

$$u(c(s)) + \beta w_s \geq u(y_s) + \beta V_{aut}$$

$$\sum \pi_s [u(c(s)) + \beta w_s] \geq w$$

$$w \in [V_{aut}, V_{\max}]$$

$$c [c_{\min}, c_{\max}]$$

foc

$$\begin{aligned}(\lambda_s + \mu\pi_s) u'(c_s) &= \pi_s \\ \lambda_s + \mu\pi_s &= -\pi_s P'(w_s)\end{aligned}$$

combing:

$$u'(c_s) = \frac{-1}{P'(w_s)}$$

since P is decreasing and concave then c_s is increasing in w_s .

- $w_s = w$ if constraint not binding $\mu = 0$
- otherwise $w_s > w$
- dynamics:
eventually converge to a high enough w so that participation constraint is not binding (this result is more general: see Debraj Ray's Econometrica paper)

4 Two Sided / GE

Sources:

- LS Chapter 15 section 413-418: good treatment of Kocherlakota (iid shocks) but no formal analysis of long-run distribution
- we follow: simplified version of Alvarez-Jermann (2000) "Quantitative Asset Pricing Implications of Endogenous Solvency Constraints". only section 4 and sub-section 5.1 (section 3 introduces the notation). This version has individual persistence of income (not necessarily iid), only 2 shocks, no aggregate shocks (in our version). We are able to study the whole dynamics.

4.1 Dynamics

- environment:
 - symmetric, two agents $i = 1, 2$; equal population

- $y^1 > y^2$, $y_t = y^1 + y^2 \equiv e$ (no aggregate uncertainty)
- aggregate state $s = 1, 2$ denotes realization of income for type 1 (equivalently: s denotes who gets high shock)
- p is probability of transition from $s = 1$ to $s = 2$ and from $s = 2$ to $s' = 1$

- Problem (recursive version)

$$V(w, s) = \max_{c^1, c^2, w'(\cdot)} \left[u(c^1) + \beta \sum_{s'} \pi[s'|s] V(w'(s'), s') \right]$$

$$\begin{aligned} c^1 + c^2 &= e \\ u(c^2) + \beta \sum \pi(s'|s) w'(s') &\geq w \\ w'(s') &\geq U_{aut}^2(s') \\ V(w'(s'), s') &\geq U_{aut}^1(s') \end{aligned}$$

- last two constraints equivalent to

$$w'(s') \in [L(s'), H(s')]$$

for some $L(s')$ and $H(s')$

- we take as given that we have V , L and H properties: V is decreasing, differentiable and concave in w we then derive some properties of the allocation
- graphical analysis: two shock case
- first order conditions:

$$\begin{aligned} u'(c^1) &= \lambda \\ \theta u'(c^2) &= \lambda \\ V_1(w'(s'), s') &\begin{matrix} \leq \\ \geq \end{matrix} -\theta \end{aligned}$$

with equality if $w'(s') \in (L(s'), H(s'))$, with \leq if $w'(s') = L(s')$ and \geq if $w'(s') = H(s')$

- Envelope condition:

$$V_1(w, s) = -\theta$$

- result 1: $c^2(w, s)$ is increasing in w

since V is concave V_1 is decreasing thus $-V_1$ is increasing in w :

$$\frac{u'(e - c^2)}{u'(c^2)} = \theta = -V_1(w, s)$$

which requires c^2 to increase with w

- result 2: if $s = s'$ then $w(s') = w$. FOC:

$$V_1(w'(s'), s') \stackrel{\leq}{\geq} -\theta = V_1(w, s)$$

is satisfied with equality if $(w'(s'), s') = (w, s)$. This satisfies the constraint since $w \in [L(s), H(s)]$ by assumption.

- result 3: in the 2 shock case if $s \neq s'$

$$V_1(w'(s'), s') \stackrel{\leq}{\geq} V_1(w, s)$$

- collecting results:

- $c^2(w, s)$ is increasing in w
- if $s' = s \rightarrow w'(s') = w$ (constraint not binding)
- if $s \neq s'$ if binding then go to closest value possible
- show graph of policy
- convergence (main result): **stationary distribution is history independent and symmetric** (we turn to studying this in more detail next)

4.2 Stationary Distributions

Given our previous result we now look for stationary symmetric distributions:

- given (c^1, c^2) let $V^1(c^1, c^2)$ and $V^2(c^1, c^2)$ be the unique solutions to:

$$\begin{aligned} V^1 &= u(c^1) + \beta [pV^1 + (1-p)V^2] \\ V^2 &= u(c^2) + \beta [pV^2 + (1-p)V^1] \end{aligned}$$

clearly: $V^2(y, x) = V^1(x, y)$

- grinding out:

$$V^1(c^1, c^2) = \frac{1}{1-\beta} \{\omega u(c^1) + (1-\omega)u(c^2)\}$$

$$\text{where } \omega = \frac{1-\beta p}{1+\beta-2p\beta} > \frac{1}{2}$$

- stationary symmetric feasible allocations satisfies:

$$c^1 + c^2 = e \tag{1}$$

$$V^1(c^1, c^2) \geq V^1(y^1, y^2) \equiv V_{aut}^1 \tag{2}$$

$$V^2(c^1, c^2) \geq V^2(y^1, y^2) \equiv V_{aut}^2 \tag{3}$$

i.e. resource constraint and participation constraints.

- substituting

$$\begin{aligned} \omega u(c^1) + (1-\omega)u(c^2) &\geq \omega u(y^1) + (1-\omega)u(y^2) \\ \omega u(c^2) + (1-\omega)u(c^1) &\geq \omega u(y^2) + (1-\omega)u(y^1) \end{aligned}$$

rearranging

$$\omega [u(c^1) - u(y^1)] + (1-\omega) [u(c^2) - u(y^2)] \geq 0 \tag{4}$$

$$(1-\omega) [u(c^1) - u(y^1)] + \omega [u(c^2) - u(y^2)] \geq 0 \tag{5}$$

if $c^1 \leq y^1$ then (4) implies (5) \Rightarrow participation constraint for type 2 never binds

- full risk sharing is attainable iff

$$u(e/2) \geq \omega^1 u(y^1) + (1-\omega^1)u(y^2)$$

- otherwise, look for allocations with:

$$c^1 + c^2 = e \tag{6}$$

$$\omega [u(c^1) - u(y^1)] + (1-\omega) [u(c^2) - u(y^2)] = 0$$

and $y^2 \leq c^2 \leq c^1 \leq y^1$ (i.e. with less variability than autarky).

- example: $u(c) = c^{1-\sigma}/(1-\sigma)$ then

$$\omega c^{1-\sigma} + (1-\omega)(e-c)^{1-\sigma} = \omega (y^1)^{1-\sigma} + (1-\omega)(y^2)^{1-\sigma}$$

- gives us $c(\omega)$ is decreasing in ω :

$$c^{1-\sigma} - (y^1)^{1-\sigma} - [(e-c)^{1-\sigma} - (y^2)^{1-\sigma}] + [\omega c^{-\sigma} - (1-\omega)(e-c)^{-\sigma}] \frac{\partial c}{\partial \omega} = 0$$

and we have $\omega(\beta, p)$ (increasing in β and p)

- implications risk sharing
 - decreasing in p
 - decreasing in β
 - increasing in risk aversion

5 Trash

5.1 Grinding $V^i(\cdot, \cdot)$ formula

From

$$\begin{aligned} V^1 &= \frac{u(c^1)}{1-\beta p} + \beta \frac{1-p}{1-\beta p} V^2 \\ V^2 &= \frac{u(c^2)}{1-\beta p} + \beta \frac{1-p}{1-\beta p} V^1 = \frac{u(c^2)}{1-\beta p} + \beta \frac{1-p}{1-\beta p} \left[\frac{u(c^1)}{1-\beta p} + \beta \frac{1-p}{1-\beta p} V^2 \right] \end{aligned}$$

we get that

$$\begin{aligned} V^2 &= \frac{u(c^2)}{1-\beta p} + \beta \frac{1-p}{(1-\beta p)^2} u(c^1) + \beta^2 \frac{(1-p)^2}{(1-\beta p)^2} V^2 \\ &= \frac{1}{(1-\beta p)^2 - \beta^2 (1-p)^2} [(1-\beta p) u(c^2) + \beta (1-p) u(c^1)] \\ &= \frac{1}{1-\beta} \left\{ \frac{1-\beta p}{1+\beta-2p\beta} u(c^2) + \frac{\beta(1-p)}{1+\beta-2p\beta} u(c^1) \right\} \end{aligned}$$

so $(1-\beta)V^2$ is a weighted average of $u(c^1)$ and $u(c^2)$.