

# NUMERICAL METHODS FOR TIME INCONSISTENCY, PRIVATE INFORMATION AND LIMITED COMMITMENT

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# MODELS WITH TIME INCONSISTENCY, PRIVATE INFORMATION AND LIMITED COMMITMENT

# WHEN STANDARD DP DOES NOT WORK

Till now, we have seen problems of the form:

$$\begin{aligned} \max_{\{u_t\}_{t=0}^{\infty}} \quad & \sum_{t=0}^{\infty} \beta^t r(x_t, u_t) \\ \text{s.t.} \quad & x_{t+1} = h(x_t, u_t), \quad t = 0, 1, \dots \\ & x_0 \in X \text{ given} \end{aligned}$$

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However there are many situations in (macro)economics that cannot be represented in the previous form.

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- DP cannot be used in cases in which (the expectations of) future behavior influence today's choices
- The problem does not satisfy a standard Bellman equation (i.e., the policy function does not depend only on state variables)
- Three categories:
  - Problems of optimal policy choice by a benevolent government which suffer from time inconsistency
  - Models of limited commitment
  - Private information environments



# CAN WE SOLVE THE PROBLEM? YES!

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- We can use a generalization of the Bellman theory
- Dynamic programming squared:
  - We transform the problem in order to introduce a new auxiliary state variable (sometimes more than one)
  - We can show that this new formulation of the problem has a recursive structure

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- Marcet and Marimon (2017): auxiliary state is derived from Lagrange multipliers
  - Very popular in optimal policy and limited commitment case
  - More recently, extended to private information environments (Sleet and Yeltekin in a series of papers) and to repeated moral hazard framework (Mele (2014))

# OPTIMAL FISCAL POLICY: HH PROBLEM

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- Representative agent, benevolent government
- Government must finance exogenous random expenditure by means of distortive taxation and debt.
- The agent solves his own maximization problem:

$$\begin{aligned} \max_{\{c_t, b_t, l_t\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t [u(c_t) + v(l_t)] \\ s.t. \quad c_t + p_t^b b_{t+1} = l_t (1 - \tau_t) + b_t \end{aligned} \quad (1)$$

# FOCs HH PROBLEM



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Substitute the budget constraint in the utility function, take FOCs:

$$/b_{t+1} : \quad p_t^b u'(c_t) = \beta E_t u'(c_{t+1}) \quad (2)$$

$$/l_t : \quad -\frac{v'(l_t)}{u'(c_t)} = (1 - \tau_t) \quad (3)$$

# GOVERNMENT'S PROBLEM

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The government wants to maximize the utility of representative agent subject to its own budget constraint, resource constraint, and **taking as given the optimal choices of the agent** summarized by equations (2)-(3) and the individual budget constraint (1):

$$\begin{aligned} \max_{\{c_t, b_t, l_t\}_{t=0}^{\infty}} \quad & E_0 \sum_{t=0}^{\infty} \beta^t [u(c_t) + v(l_t)] \\ \text{s.t.} \quad & (1), (2), (3) \end{aligned}$$

$$c_t + g_t = l_t \tag{4}$$

$$g_t + p_t^b b_{t+1}^g = b_t^g + \tau_t l_t \tag{5}$$

$$b_t^g + b_t = 0 \tag{6}$$

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$$\begin{aligned} \max_{\{c_t, b_t, l_t\}_{t=0}^{\infty}} \quad & E_0 \sum_{t=0}^{\infty} \beta^t [u(c_t) + v(l_t)] \\ \text{s.t.} \quad & c_t - \beta \frac{E_t u'(c_{t+1})}{u'(c_t)} b_{t+1}^g = -(c_t + g_t) \frac{v'(c_t + g_t)}{u'(c_t)} - b_t^g \end{aligned}$$

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The optimal choice of  $c_t$  depends on the value of  $c_{t+1}$

# ONE-SIDED LACK OF COMMITMENT

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- Risk neutral Principal, risk averse Agent
- Agent receive  $y_t$  each period
- Principal borrows and lends at interest rate  $R = \beta^{-1}$ , agent cannot save and has no access to credit market
- Principal and agent want to share the risk associated with endowment
- write a contract at time 0, that defines the sharing rule for each period  $t$  and each possible realization of the endowment process



# ONE-SIDED LACK OF COMMITMENT (CONT.)

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- Principal is a nice guy and can commit forever to stay in the risk-sharing contract
- Agent is not a loyal guy, and can leave the arrangement at any time, being at that point on his own and having to consume just his individual endowment
- write a contract such that the risk-sharing rule gives always the agent a sufficient amount to stay in the agreement

# ONE-SIDED LACK OF COMMITMENT (CONT.)

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**Participation constraint** makes sure the value of staying in the contract for the agent is always larger than the value of the contract in autarky (i.e., consuming only his own endowment):

$$\begin{aligned}
 & \max_{\{c_t\}_{t=0}^{\infty}} E_{-1} \sum_{t=0}^{\infty} \beta^t (y_t - c_t) \\
 & s.t. \quad u(c_t) + \beta E_t \sum_{j=1}^{\infty} \beta^{j-1} u(c_{t+j}) \geq \\
 & \quad u(y_t) + \beta E_t \sum_{j=1}^{\infty} \beta^{j-1} u(y_{t+j}), \quad t = 0, 1, \dots
 \end{aligned} \tag{7}$$

# ENDOWMENT IS PRIVATE INFORMATION

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- Assume full commitment but endowment is agent's private information
- Revelation principle  $\Rightarrow$  truthful revelation mechanisms
- The principal chooses transfers  $\tau_t(y^t) \equiv c_t(y^t) - y_t$  trying to minimize the expected discounted cost of implementing an incentive compatible allocation.
- Let  $y \in \{\bar{y}_i\}_{i=1}^N$  such that  $\bar{y}_i < \bar{y}_{i+1}$  for any  $i$ .

# INCENTIVE COMPATIBILITY

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Define the local downward incentive-compatibility constraints as

$$DIC_t \left( y^{t-1}, \bar{y}_i; \bar{y}_{i-1} \right) = \left\{ \beta^t \left[ u \left( c_t \left( y^{t-1}, \bar{y}_i \right) \right) + \beta U_{t+1} \left( y^{t-1}, \bar{y}_i \right) - \right. \right. \\ \left. \left. - u \left( c_t \left( y^{t-1}, \bar{y}_{i-1} \right) \right) - \beta U_{t+1} \left( y^{t-1}, \bar{y}_{i-1} \right) \right] \right\} \\ \forall y^{t-1}, \quad \forall \bar{y}_i, \quad i = 2, \dots, N$$

where

$$U_{t+1} \left( y^{t-1}, \bar{y}_i \right) \equiv \sum_{j=1}^{\infty} \sum_{y^{t+j} \in Y^{t+j+1}} \beta^{j-1} u \left( c_{t+j} \left( y^{t-1}, \bar{y}_i, y^{t+j} \right) \right) \pi \left( y^{t+j} | y_{-1} \right)$$



# OPTIMAL CONTRACT

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I can solve a relaxed Pareto-constrained problem in which I only impose the local downward incentive-compatibility constraints (I need to impose some strong concavity conditions)

$$\max_{\{\tau_t(y^t)\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \sum_{y^t \in Y^{t+1}} \beta^t \left[ -\tau_t(y^t) \right] \pi(y^t | y_{-1})$$

$$s.t. \quad \sum_{t=0}^{\infty} \sum_{y^t \in Y^{t+1}} \beta^t u(c_t(y^t)) \pi(y^t | y_{-1}) \geq U_0$$

$$DIC_t(y^{t-1}, \bar{y}_i; \bar{y}_{i-1}) \geq 0 \quad \forall y^{t-1}, \quad \forall \bar{y}_i, \quad i = 2, \dots, N$$

# HIDDEN EFFORT

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- Endowment is observable and i.i.d.
- Its future distribution is affected by an unobservable agent's action  $a_t$  through the transition function  $\pi(y_{t+1} \mid a_t)$
- $a_t$  is costly for the agent:

$$u(c_t(y^t)) - v(a_t(y^t))$$

# OPTIMAL CONTRACT

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We can characterize the optimal contract by solving:

$$\begin{aligned}
 & \max_{\{\tau_t(y^t)\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \sum_{y^t \in Y^{t+1}} \beta^t \left[ -\tau_t(y^t) \right] \pi \left( y^t \mid a^{t-1}(y^{t-1}) \right) \\
 & s.t. \sum_{t=0}^{\infty} \sum_{y^t \in Y^{t+1}} \beta^t \left[ u(c_t(y^t)) - v(a_t(y^t)) \right] \pi \left( y^t \mid a^{t-1}(y^{t-1}) \right) \geq U_0 \\
 & \left\{ a_t(y^t) \right\}_{t=0}^{\infty} \in \arg \max_{\{a_t(y^t)\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \sum_{y^t \in Y^{t+1}} \beta^t \left[ u(c_t(y^t)) - v(a_t(y^t)) \right] \times \\
 & \quad \pi \left( y^t \mid a^{t-1}(y^{t-1}) \right)
 \end{aligned}$$

# THE PROMISED UTILITIES APPROACH

# THE APPROACH OF ABREU PEARCE AND STACCHETTI

- Main idea in DP: we make the problem recursive by summarizing all the history in a state variable
- In non-DP problems: not possible, therefore decisions today depend on the whole past history



# THE APPROACH OF ABREU PEARCE AND STACCHETTI

- Main idea in DP: we make the problem recursive by summarizing all the history in a state variable
- In non-DP problems: not possible, therefore decisions today depend on the whole past history
- Look for a variable that summarizes history
- APS says: use continuation values of the individuals (costate variable)
- Continuation value summarizes the promises that the planner made to the agent in the past

# THE APPROACH OF ABREU PEARCE AND STACCHETTI

- Given continuation value promised yesterday, planner chooses future continuation value
- Choosing a future continuation value means choosing a promise to the agent
- New continuation values must be consistent with promises made in the past, and with all the remaining constraints of the problem

# APS FOR SUBGAME PERFECT EQUILIBRIA

- $N$  players, choose an action  $a_i \in A$  in each period

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- Each player observes  $h_{i,t}$  in each period
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- Strategy profile:  $\sigma_i$  generates a sequence of action profiles

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$$v_i(\sigma) = \sum_{t=0}^{\infty} \beta^t u_i(a^t)$$



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$$v_i(\sigma) = \sum_{t=0}^{\infty} \beta^t u_i(a^t)$$

- profile of continuation strategies for the subgame starting at  $h^t$ :  $\sigma |_{h^t}$

$$v_i(\sigma |_{h^t}) = \sum_{j=t}^{\infty} \beta^{j-t} u_i(a^j)$$

# SUBGAME PERFECT EQUILIBRIA

## DEFINITION 1

$\sigma^*$  is a subgame perfect equilibrium if, for any  $h^t$ ,  $\sigma|_{h^t}$  is Nash of the subgame starting at  $h^t$ .

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## DEFINITION 2

Let  $W \subset \mathbb{R}^N$ . Then  $(a, v)$  is admissible with respect to  $W$  if  $a \in A$ ,  $v \in W$  and

$$u_i(a) + \beta v_i(a) \geq u_i(\hat{a}_i, a_{-i}) + \beta v_i(\hat{a}_i, a_{-i}) \quad \forall \hat{a}_i \quad \forall i$$

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Let  $B(W)$  be the set of all values of admissible pairs for  $W$

# SELF-GENERATION AND FACTORIZATION

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*(Factorization)  $V = B(V)$*

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## THEOREM 4

**(Factorization)**  $V = B(V)$

The set of equilibrium values is a fixed point of the set-valued operator  $B$



# CALCULATING $V$

## THEOREM 5

*Let  $W_0 \subseteq \mathbb{R}^N$  be compact and such that  $V \subseteq B(W_0) \subseteq W_0$ . For  $n = 1, 2, \dots$ , let  $W_n = B(W_{n-1})$ . Then  $\{W_n\}$  is a decreasing sequence and  $V = \lim_{n \rightarrow \infty} W_n$ .*

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We can follow this procedure:

- 1 Start with a set  $W_0 \subseteq \mathbb{R}^N$  such that  $V \subseteq B(W_0) \subseteq W_0$ .
- 2 For any  $n = 1, 2, \dots$ , calculate  $W_n = B(W_{n-1})$
- 3 Iterate until convergence.

# GENERAL APPLICABILITY

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- We can generate the set of all payoffs that satisfy certain constraints by applying Theorem 5
- We are typically interested in efficient equilibria
- Standard application of APS has two stages: first, get the set of continuation values that satisfy some constraints, and then look for the efficient ones in that set

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- We will look at one way to do it for repeated games, which has given rise to lot of extensions for more complicated problems
- Conklin, Judd and Yeltekin (2003)

# CHARACTERIZATION OF THE FEASIBLE SET

## SETUP

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- Player  $i$ 's payoff in the stage game will be  $\Pi_i : A_i \rightarrow \mathbf{R}$ .
- Player  $i$  responds optimally to other players' actions, getting a payoff given by

$$\Pi_i^*(a_{-i}) \equiv \max_{a_i \in A_i} \Pi_i(a_i, a_{-i})$$

# CHARACTERIZATION OF THE FEASIBLE SET

## THE $B$ OPERATOR

Define  $B(W)$  as

$$B(W) = \bigcup_{(a,w) \in A \times W} \{(1 - \delta)\Pi(a) + \delta w \mid \forall i (IR_i \geq 0)\}$$

where

$$IR_i \equiv [(1 - \delta)\Pi(a) + \delta w_i] - [(1 - \delta)\Pi^*(a_{-i}) + \delta \underline{w}_i]$$

is the individual rationality constraint for player  $i$ , and

$$\underline{w}_i \equiv \inf_{w \in W} w_i$$

is player  $i$ 's worst possible continuation value in  $W$ .

# CHARACTERIZATION OF THE FEASIBLE SET

## OUTER AND INNER APPROXIMATION

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## OUTER AND INNER APPROXIMATION

- **Outer Approximation.**  $W$  is the convex combination of a finite number of half-spaces which can be represented as a collection of linear inequalities. In this case,  $W = \bigcap_{\ell=1}^L \{z \in \mathbf{R}^N \mid h_{\ell}z \leq c_{\ell}\}$  where  $h_{\ell} \in \mathbf{R}^N$  is the gradient orthogonal to the face  $\ell$  of  $W$ , and  $c_{\ell} \in \mathbf{R}$  is a scalar which we call a level.

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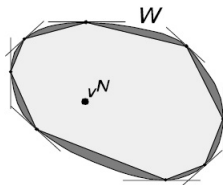
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- **Inner Approximation.**  $W$  is approximated as the convex hull of some finite number of vertices  $Z$ , that is  $W = co(Z)$ , the convex hull of  $Z$ .

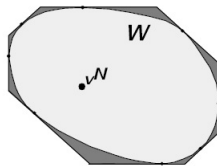
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(a) Inner Approx.



(b) Outer Approx.



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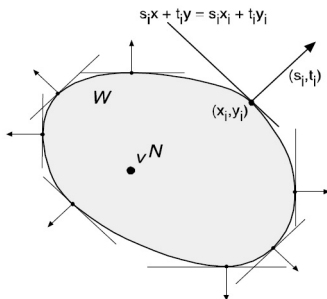
- Suppose we know  $N$  points on the boundary of  $W$ , call them  $Z = \{z_1, z_2, \dots, z_N\}$ , and the corresponding subgradients  $G = \{g_1, g_2, \dots, g_N\}$ . In other words, the hyperplane  $z_i \cdot g_i = z \cdot g_i$  is tangent to  $W$  at  $z_i$ , and the gradients are such that  $g_i \cdot w \leq g_i \cdot z_i$  for  $w \in W$ .

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## OUTER APPROXIMATION



In the graph,  $z_i = (x_i, y_i)$ ,  $g_i = (s_i, t_i)$ . Each tangent hyperplane generates two half-spaces. The one containing  $W$  is called the interior half-space. The outer approximation is therefore the intersection of all the interior half-spaces generated by all  $z_i$ 's, and it is in fact the smallest convex set containing  $W$ , given our choice of  $Z$  and  $G$ .

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## RAY AND EXTREMAL PROCEDURES

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- Ray procedure: (for inner approx.)
- Extremal procedure: (for both)

# CHARACTERIZATION OF THE FEASIBLE SET

## RAY AND EXTREMAL PROCEDURES

- Ray procedure: (for inner approx.)
  - choose point  $v^N$  in the set  $W$
  
- Extremal procedure: (for both)

# CHARACTERIZATION OF THE FEASIBLE SET

## RAY AND EXTREMAL PROCEDURES

- Ray procedure: (for inner approx.)
  - choose point  $v^N$  in the set  $W$
  - $\theta$  = polar coordinate angle from  $v^N$
  
- Extremal procedure: (for both)



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## RAY AND EXTREMAL PROCEDURES

- Ray procedure: (for inner approx.)
  - choose point  $v^N$  in the set  $W$
  - $\theta$  = polar coordinate angle from  $v^N$
  - Choose a set of  $\theta$ 's and find rays at angle  $\theta$  that intersect the boundary of  $W$
- Extremal procedure: (for both)

# CHARACTERIZATION OF THE FEASIBLE SET

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- Also a linear programming problem
- Repeating the same maximization for several subgradients, we can generate a set of pairs  $(Z, G)$ . In fact, when  $Z$  is available, we can use it for calculating the inner approximation as the convex hull of  $Z$ .

# CHARACTERIZATION OF THE FEASIBLE SET

## OUTER MONOTONE APPROXIMATION OF $B(W)$

---

### Algorithm 1: Outer Monotone Approximation of $B(W)$

- 1 Define  $L$  search subgradients  $H = \{h_1, h_2, \dots, h_L\} \subset R^N$
  - 2 Define  $W$  with  $M$  approximation subgradients  $G = \{g_1, g_2, \dots, g_M\} \subset R^N$  and levels  $C = \{c_m \mid m = 1, \dots, M\} \subset R$  such that
$$W \equiv \bigcap_{\ell=1}^M \{z \mid g_m \cdot z \leq c_m\}$$
-

# CHARACTERIZATION OF THE FEASIBLE SET

## OUTER MONOTONE APPROXIMATION OF $B(W)$

3 For each  $h_\ell \in H$ :

- 1 For each  $a \in A$ , find optimal feasible equilibrium value in the  $h_\ell$  direction, by assuming that action  $a$  is the current action profile, by solving

$$\begin{aligned} c_\ell(a) &= \max_w h_\ell \cdot [(1 - \delta)\Pi(a) + \delta w] \\ w &\in W \\ (1 - \delta)\Pi^i(a) + \delta w_i &\geq (1 - \delta)\Pi_i^*(a_{-i}) + \delta \underline{w}_i \\ i &= 1, \dots, N \end{aligned} \quad (8)$$

and set  $c_\ell(a) = -\infty$  if there is no  $w$  that satisfies the constraint (8)

- 2 Choose the best action profile  $a \in A$  by computing

$$c_\ell^+ = \max\{c_\ell(a) \mid a \in A\}$$

- 4 Get  $B^O(W; H) = W^+$ , where levels are in  $C^+ = \{c_1^+, \dots, c_L^+\}$ , the approximation gradients are in  $H$  and  $W^+ = \bigcap_{\ell=1}^L \{z \mid g_\ell \cdot z \leq c_\ell^+\}$

# CHARACTERIZATION OF THE FEASIBLE SET

## OUTER HYPERPLANE ALGORITHM FOR APPROXIMATING $V$

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### Algorithm 2: Outer Hyperplane Algorithm for Approximating $V$

- ➊ Set initial guess  $W^0 \supset \mathcal{W}$  and the elements of the approximation:
    - ➊ Set  $L$  search subgradients  $H = \{h_1, h_2, \dots, h_L\} \subset R^N$
    - ➋ Select boundary points  $Z^0 = \{z_1^0, \dots, z_L^0\} \subset R^N$
    - ➌ Compute hyperplane levels  $c_\ell^0 = g_\ell^0 \cdot z_\ell^0$ ,  $\ell = 1, \dots, L$  and collect them in  $C^0$
    - ➍ Let  $W^0 = \bigcap_{\ell=1}^L \{z \mid g_\ell \cdot z \leq c_\ell^0\}$
  - ➋ Generate  $W^{k+1} = B^O(W^k; H)$ , where  $C^{k+1} = \{c_1^{k+1}, \dots, c_L^{k+1}\}$  define  $W^{k+1} = \bigcap_{\ell=1}^L \{z \mid g_\ell \cdot z \leq c_\ell^{k+1}\}$
  - ➌ Stop if  $W^{k+1}$  is close to  $W^k$ , i.e. if  $\max_\ell |c_\ell^{k+1} - c_\ell^k| < \varepsilon$ .
-



# CHARACTERIZATION OF THE FEASIBLE SET

## MONOTONE INNER HYPERPLANE APPROXIMATION OF $B(W)$

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### Algorithm 3: Monotone Inner Hyperplane Approximation of $B(W)$

- ① Define  $L$  search subgradients  $H = \{h_1, h_2, \dots, h_L\} \subset R^N$
  - ② Define  $W$  with  $M$  approximation subgradients  $G = \{g_1, g_2, \dots, g_M\} \subset R^N$  and levels  $C = \{c_m \mid m = 1, \dots, M\} \subset R$  such that
$$W \equiv \bigcap_{\ell=1}^M \{z \mid g_m \cdot z \leq c_m\}$$
-

# CHARACTERIZATION OF THE FEASIBLE SET

## MONOTONE INNER HYPERPLANE APPROXIMATION OF $B(W)$

③ For each  $h_\ell \in H$ :

- ① For each  $a \in A$ , find optimal feasible equilibrium value in the  $h_\ell$  direction by solving

$$c_\ell(a) = \max_{\substack{w \\ w \in W}} h_\ell \cdot [(1 - \delta)\Pi(a) + \delta w]$$

$$(1 - \delta)\Pi^i(a) + \delta w_i \geq (1 - \delta)\Pi_i^*(a_{-i}) + \delta \underline{w}_i \quad (9)$$

$$i = 1, \dots, N$$

and set  $c_\ell(a) = -\infty$  if there is no  $w$  that satisfies the constraint (9)

- ② Choose the best action profile  $a \in A$  and the corresponding continuation value:

$$a_\ell^* = \arg \max \{c_\ell(a) \mid a \in A\}$$

$$z'_\ell = (1 - \delta)\Pi^i(a_\ell^*) + \delta w_\ell(a_\ell^*)$$

- ③ Collect set of vertices of convex hull  $Z' = \{z'_\ell \mid \ell = 1, \dots, L\}$  and define  $W^+ = co(Z')$

# CHARACTERIZATION OF THE FEASIBLE SET

## MONOTONE INNER HYPERPLANE APPROXIMATION OF $B(W)$

- ④ Compute  $Z^+ = \{z' \in Z' \mid z' \in \partial W^+\}$ , and find subgradients  $G^+ = \{g_1^+, g_2^+, \dots, g_M^+\} \subset R^N$  and levels  $C^+ = \{c_m^+ \mid m = 1, \dots, M\} \subset R$  such that  $co(Z^+) \equiv \bigcap_{\ell=1}^M \{z \mid g_m^+ \cdot z \leq c_m^+\} = W^+$
  - ⑤ Get  $B^I(W; H) = W^+$ , where levels are in  $C^+ = \{c_1^+, \dots, c_L^+\}$ , the approximation subgradients are in  $G^+$  and vertices are in  $Z^+$
-

# CHARACTERIZATION OF THE FEASIBLE SET

## CONCEPT OF DISTANCE USED BY CJY

To define convergence for the inner approximation iterations, CJY use the following distance:

$$d(Z_1, Z_2) = \max \left\{ \max_{z_1 \in Z_1} \min_{z_2 \in Z_2} \|z_1 - z_2\|, \max_{z_2 \in Z_2} \min_{z_1 \in Z_1} \|z_1 - z_2\| \right\} \quad (10)$$

# CHARACTERIZATION OF THE FEASIBLE SET

## INNER HYPERPLANE ALGORITHM FOR APPROXIMATING $V$

---

### Algorithm 4: Inner Hyperplane Algorithm for Approximating $V$

- ① Set initial elements of the approximation:
    - ① Set  $L$  search subgradients  $H = \{h_1, h_2, \dots, h_L\} \subset R^N$
    - ② Select vertices  $Z^0 = \{z_1^0, \dots, z_M^0\} \subset R^M$  for initial guess  $W^0 = co(Z^0)$
    - ③ Define the gradients  $G = \{g_1^0, \dots, g_M^0\} \subset R^M$  and levels  $C^0 = \{c_1^0, \dots, c_M^0\} \subset R^M$  which define  $W^0 = \bigcap_{m=1}^M \{z \mid g_m^0 \cdot z_m^0 \leq c_m^0\}$
  - ② Generate  $W^{k+1} = B^I(W^k; H)$ , with vertices  $Z^{k+1} = \{z_1^{k+1}, \dots, z_M^{k+1}\}$
  - ③ Stop if  $d(Z^{k+1}, Z^k) < \varepsilon$
-

# CHARACTERIZATION OF THE FEASIBLE SET

## REPEATED PRISONER'S DILEMMA

Discount factor  $\delta = 0.8$

Payoffs of the prisoner's dilemma:

		player 2	
		Actions	
		C	D
player 1	C	(4,4)	(0,6)
	D	(6,0)	(2,2)

# ONE-SIDED LACK OF COMMITMENT

$$\begin{aligned}
 & \max_{\{c_t\}_{t=0}^{\infty}} && E_{-1} \sum_{t=0}^{\infty} \beta^t (y_t - c_t) \\
 & s.t. && E_{-1} \sum_{t=0}^{\infty} \beta^t u(c_t) \geq U_0 \\
 & && u(c_t) + \beta E_t \sum_{j=1}^{\infty} \beta^{j-1} u(c_{t+j}) \geq u(y_t) + \beta U_{aut} \forall t \quad (11)
 \end{aligned}$$

Assume  $y_t$  is i.i.d. and its support is  $\mathbf{Y} \equiv \{\bar{y}_s\}_{s=1}^S$ . Call its distribution function  $\pi_s, s = 1, \dots, S$ .

# PROMISED UTILITY

Define the *agent's promised utility* as:

$$U_t \equiv E_{t-1} \sum_{j=0}^{\infty} \beta^j u(c_{t+j}) \quad (12)$$

This variable summarizes the promises that the principal makes to the agent in each period.



# RECURSIVE CONTRACT

- Principal enters period  $t$  with a promise  $U_-$  made in  $t - 1$
- Complies with previous promise by choosing state-contingent consumption  $c_s, s = 1, \dots, S$  and a new promise  $U_s, s = 1, \dots, S$
- Let  $P(U_-)$  be the value function of the principal:

$$P(U_-) = \max_{\{c_s, U_s\}_{s=1}^S} \sum_{s=1}^S \pi_s [\bar{y}_s - c_s + \beta P(U_s)] \quad (13)$$

$$s.t. \quad \sum_{s=1}^S \pi_s [u(c_s) + \beta U_s] \geq U_- \quad (14)$$

$$u(c_s) + \beta U_s \geq u(\bar{y}_s) + \beta U_{aut} \quad s = 1, \dots, S \quad (15)$$

$$c_s \in C \quad (16)$$

$$U_s \in \mathcal{U} \quad (17)$$

# THE SET $\mathcal{U}$

The set  $\mathcal{U}$  is obtained iterating on the APS operator  $B$  defined as:

$$B(W) = \left\{ \begin{array}{l} U \in W : \sum_{s=1}^S \pi_s [u(c_s) + \beta U_s] \geq U, \\ u(c_s) + \beta U_s \geq u(\bar{y}_s) + \beta U_{aut} \quad s = 1, \dots, S \\ c_s \in C \quad s = 1, \dots, S \end{array} \right\} \quad (18)$$

# GETTING A SOLUTION

Apart from this set, the functional equation looks like a Bellman equation in which we have the agent's value function as a state variable. Therefore, we can characterize the optimal contracts in two steps:

- 1 Find the set  $\mathcal{U}$  by repeatedly applying the operator  $B$  defined in (18)
- 2 Solve the Bellman equation as usual, either with value function iteration or Howard's improvement algorithm.

# ENDOWMENT IS PRIVATE INFORMATION

$$\begin{aligned}
 & \max_{\{\tau_t(y^t)\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \sum_{y^t \in Y^{t+1}} \beta^t \left[ -\tau_t(y^t) \right] \pi(y^t | y_{-1}) \\
 & \quad s.t. \quad \sum_{t=0}^{\infty} \sum_{y^t \in Y^{t+1}} \beta^t u(c_t(y^t)) \pi(y^t | y_{-1}) \geq U_0 \\
 & \quad \quad \quad DIC_t(y^{t-1}, \bar{y}_i; \bar{y}_{i-1}) \geq 0 \quad \forall y^{t-1}, \quad \forall \bar{y}_i, \quad i = 2, \dots, N
 \end{aligned}$$

# RECURSIVE CONTRACT

$$P(U_-) = \max_{\{\tau_s, U_s\}_{s=1}^S} \sum_{s=1}^S \pi_s [-\tau_s + \beta P(U_s)] \quad (19)$$

$$s.t. \quad \sum_{s=1}^S \pi_s [u(\tau_s + \bar{y}_s) + \beta U_s] = U_- \quad (20)$$

$$u(\tau_s + \bar{y}_s) + \beta U_s \geq u(\tau_{s-1} + \bar{y}_s) + \beta U_{s-1} \quad s = 2, \dots, S \quad (21)$$

$$c_s \in C \quad (22)$$

$$U_s \in \mathcal{U} \quad (23)$$

# THE SET $\mathcal{U}$

$\mathcal{U}$  is the fixed point of the operator:

$$B(W) = \left\{ \begin{array}{l} U \in W : \sum_{s=1}^S \pi_s [u(\tau_s + \bar{y}_s) + \beta U_s] \geq U, \\ u(\tau_s + \bar{y}_s) + \beta U_s \geq u(\tau_{s-1} + \bar{y}_s) + \beta U_{s-1} \quad s = 2, \dots, S \\ c_s \in C \quad s = 1, \dots, S \end{array} \right\} \quad (24)$$

# HIDDEN EFFORT

$$\begin{aligned}
 & \max_{\{\tau_t(y^t)\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \sum_{y^t \in Y^{t+1}} \beta^t \left[ -\tau_t(y^t) \right] \pi(y^t \mid a^{t-1}(y^{t-1})) \\
 & \text{s.t.} \quad \sum_{t=0}^{\infty} \sum_{y^t \in Y^{t+1}} \beta^t \left[ u(c_t(y^t)) - v(a_t(y^t)) \right] \pi(y^t \mid a^{t-1}(y^{t-1})) \geq U_0 \\
 & \quad \{a_t(y^t)\}_{t=0}^{\infty} \in \arg \max_{\{a_t(y^t)\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \sum_{y^t \in Y^{t+1}} \beta^t \left[ u(c_t(y^t)) - v(a_t(y^t)) \right] \pi(y^t \mid a^{t-1}(y^{t-1}))
 \end{aligned}$$

# RECURSIVE CONTRACT

$$P(U_-, \bar{y}_i) = \max_{\{c, \{U_s\}_{s=1}^S, a^*\}} \left[ \bar{y}_i - c + \beta \sum_{s=1}^S \pi_s(a^*) P(U_s, \bar{y}_s) \right] \quad (25)$$

$$s.t. \quad u(c) - v(a^*) + \beta \sum_{s=1}^S \pi_s(a^*) U_s = U_- \quad (26)$$

$$a^* = \arg \max_{a \in A} \left\{ u(c) - v(a) + \beta \sum_{s=1}^S \pi_s(a) U_s \right\} \quad (27)$$

$$c \in C, a \in A \quad (28)$$

$$U_s \in \mathcal{U} \quad (29)$$

Notice different timing convention: effort affects the probability of the state tomorrow



# THE SET $\mathcal{U}$

$\mathcal{U}$  is the fixed point of the operator:

$$B(W) = \left\{ \begin{array}{l} U \in W : u(c) - v(a^*) + \beta \sum_{s=1}^S \pi_s(a^*) U_s = U, \\ a^* = \arg \max_{a \in A} \left\{ u(c) - v(a) + \beta \sum_{s=1}^S \pi_s(a) U_s \right\} \\ c \in C, a \in A \quad s = 1, \dots, S \end{array} \right\} \quad (30)$$

# OPTIMAL FISCAL POLICY

$$\begin{aligned}
 & \max_{\{c_t, b_t, l_t\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t [u(c_t) + v(l_t)] \\
 & \text{s.t.} \quad c_t - \beta \frac{E_t u'(c_{t+1})}{u'(c_t)} b_{t+1}^g = -(c_t + g_t) \frac{v'(c_t + g_t)}{u'(c_t)} - b_t^g
 \end{aligned}$$

## OPTIMAL FISCAL POLICY (CONT.)

Small departure from APS:

- Instead of using the continuation value of the agent as a state variable, we are going to use the marginal utility of consumption
- We have already a state variable in this problem: debt holdings.
- We have to characterize a feasible set for continuation values for any value of debt holdings: i.e. a correspondence

# RECURSIVE CONTRACT

Let  $m \equiv u'(c)$ , govt expenditure can take  $S$  values and is i.i.d. as in previous examples

$$P(m_-, \bar{g}_s, b_-) = \max_{\{c, b, l, \{m_s\}_{s=1}^S\}} u(c) + v(l) + \beta \sum_{s=1}^S P(m_s, \bar{g}_s, b) \quad (31)$$

$$s.t. \quad c - \beta \frac{\sum_{s=1}^S m_s}{m_-} b = -(c + \bar{g}_s) \frac{v'(c + \bar{g}_s)}{m_-} - b_- \quad (32)$$

$$c \in C, l \in L, b \in B \quad (33)$$

$$m_s \in \mathcal{U}(b_-) \quad (34)$$

# THE SET $\mathcal{U}(b_-)$

$\mathcal{U}(b_-)$  is the fixed point of the operator

$$B(W(b_-)) = \left\{ \begin{array}{l} m \in W(b_-) : c - \beta \frac{\sum_{s=1}^S m_s}{m_-} b = -(c + \bar{g}_s) \frac{v'(c + \bar{g}_s)}{m_-} - b_- \\ c \in C, l \in L, b \in B \end{array} \right\} \quad (35)$$

This set changes as  $b_-$  changes

$$DP^2 = (\text{CURSE OF DIMENSIONALITY})^2$$

- Any application can be solved by a two-step procedure:
  - 1 Characterize the set of continuation values
  - 2 Solve the Bellman equation
- First step causes many troubles if other ("natural") state variables or several agents (e.g., optimal fiscal policy)
- Set of admissible continuation values is a correspondence that maps from the set of natural states to the set of continuation values
- I don't know any paper that works with more than 2 natural states