### G5212: Game Theory

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### Adverse Selection

- Last lecture we discussed a specific model of adverse selection
  - Two types for the agent
- This gave us a lot of intuition
  - Indeed, there were many lessons that will turn out to be general

### The Second Best Contract

- Summarizing the second best contract
  - High type gets efficient allocation
  - Every type is indifferent between their contract and that of the type immediately below
  - All types but the lowest get positive surplus (informational rent)
  - All types but the highest get less than efficient allocation
  - Lowest type gets zero surplus

### Adverse Selection

- However, it was also rather specific
- Today we will solve a more general model
  - Agent has a type  $\theta \in [\theta_1, \theta_2]$  continuous type space
  - Distributed according to continuous pdf f with cdf F
  - Principal and agent will exchange a bundle of goods q for payment t
  - Utility of principal

• Utility of agent of type  $\theta$ 

$$U(q,t,\theta) = U(q,\theta) - t$$

• We will assume model is parameterized in such a way that all types are sold to

# Optimality

• As in the previous model we can assume that the principal offers the agent a set of contracts

 $q(\theta),\,t(\theta)$ 

Which is the bundle of goods and price designed for the agent of type  $\theta$ 

- Two types of constraints must hold:
- Individual rationality: Each type of agent must prefer their contract to the outside option (which we normalize to 0)

 $U(q(\theta), t(\theta), \theta) \ge 0$ 

• Incentive Compatibility: Each agent must prefer their own contract to any other

$$U(q(\theta), t(\theta), \theta) \ge U(q(\hat{\theta}), t(\hat{\theta}), \theta)$$

## Incentive Compatibility

- We will start by analyzing the IC constraints
- Define

$$V( heta, \hat{ heta}) = U(q(\hat{ heta}), t(\hat{ heta}), heta)$$

Utility of an agent of type  $\theta$  who announces  $\hat{\theta}$ 

• IC constraint says, for all  $\theta \in [\theta_1, \theta_2]$ 

 $V(\theta,\theta) \geq V(\theta,\hat{\theta})$ 

### First and Second Order Conditions

- This means that  $V(\theta, \theta)$  must be an optimum of  $V(\theta, \hat{\theta})$
- We will assume that the mechanism is differentiable
- $\bullet\,$  If so, necessary conditions are, for all  $\theta$ 
  - First order conditions

$$\frac{\partial V}{\partial \hat{\theta}}\Big|_{\hat{\theta}=\theta} \left(\theta, \hat{\theta}\right) = 0$$

• Second order conditions

$$\left. \frac{\partial^2 V}{\partial \hat{\boldsymbol{\theta}}^2} \right|_{\hat{\boldsymbol{\theta}} = \boldsymbol{\theta}} (\boldsymbol{\theta}, \hat{\boldsymbol{\theta}}) \leq 0$$

## First Order Condition

$$\frac{\partial V}{\partial \hat{\theta}}\Big|_{\hat{\theta}=\theta} \left(\theta, \hat{\theta}\right) = 0$$

• This implies

$$\frac{\partial}{\partial \hat{\theta}} \bigg|_{\hat{\theta} = \theta} \left( U(q(\hat{\theta}), \theta) - t(\hat{\theta}) \right) = 0$$

• or

$$t'(\hat{ heta}) = rac{\partial U(q(\hat{ heta}), heta)}{\partial q} q'\left(\hat{ heta}
ight)$$

• For  $\hat{\theta} = \theta$ 

## Second Order Condition

$$\frac{\partial^2 V}{\partial \hat{\theta}^2} \Big|_{\hat{\theta} = \theta} \left( \theta, \hat{\theta} \right) \le 0$$

• This implies

$$\left. \frac{\partial^2}{\partial \hat{\boldsymbol{\theta}}^2} \right|_{\hat{\boldsymbol{\theta}} = \boldsymbol{\theta}} \left[ U(\boldsymbol{q}(\hat{\boldsymbol{\theta}}), \boldsymbol{\theta}) - t(\hat{\boldsymbol{\theta}}) \right] \leq 0$$

• or

$$t''(\hat{\theta}) \ge \frac{\partial U(q(\hat{\theta}), \theta)}{\partial q} q''(\hat{\theta}) + \frac{\partial^2 U(q(\hat{\theta}), \theta)}{\partial q^2} \left(q'(\hat{\theta})\right)^2$$

• For  $\hat{\theta} = \theta$ 

### Second Order Condition

- $\bullet$  Notice that the FOC must hold for every  $\theta$
- So differentiate WRT  $\theta$ , taking into account that  $\hat{\theta}$  must move 1-1 with  $\theta$

$$t'(\hat{ heta}) = rac{\partial U(q(\hat{ heta}), heta)}{\partial q}q'\left(\hat{ heta}
ight)$$

• implies

$$\begin{split} t''(\hat{\theta}) &= \frac{\partial U(q(\hat{\theta}), \theta)}{\partial q} q''\left(\hat{\theta}\right) \\ &+ \frac{\partial^2 U(q(\hat{\theta}), \theta)}{\partial q^2} \left(q'(\hat{\theta})\right)^2 \\ &+ \frac{\partial^2 U(q(\hat{\theta}), \theta)}{\partial q \partial \theta} q'(\hat{\theta}) \end{split}$$

## Second Order Condition

• Substituting back in to the SOC gives

$$\frac{\partial^2 U(q(\hat{\theta}), \theta)}{\partial q \partial \theta} \bigg|_{\theta = \hat{\theta}} q'(\hat{\theta}) \ge 0$$

• This gives us two conditions stemming from the FOC and SOC of the IC constraints for  $\hat{\theta} = \theta$ 

$$t'(\hat{\theta}) = \frac{\partial U(q(\hat{\theta}), \theta)}{\partial q} q'\left(\hat{\theta}\right)$$

• IC2

$$\frac{\partial^2 U(q(\hat{\theta}),\theta)}{\partial q \partial \theta} q'(\hat{\theta}) \geq 0$$

## Second Order Condition

• Notice that IC2 depends crucially on

 $\frac{\partial^2 U(q(\hat{\theta}),\theta)}{\partial q \partial \theta}$ 

- Which is a property of the utility function
- Life becomes much easier if we assume that this has the same sign everywhere
  - e.g. it is strictly positive

## Second Order Condition

- This is the Spence/Mirrlees condition
  - Also known as the single crossing condition
- It has economic content:
- Means (for example) that

$$\frac{\partial U(q,\theta)}{\partial q}$$

is always increasing in type

- The marginal utility of an increase in q is always higher for a higher type
  - or, in other words, the willingness to pay for an increase in q is always higher for higher types

# Single Crossing



• For  $\theta_2 > \theta_1$ 

- Why does Spence-Mirrlees imply single crossing?
- Equation for the type i indifference curve

$$t(q,\theta) = U(q,\theta_i) - K$$

• Slope is therefore given by

$$\frac{\partial U(q,\theta)}{\partial q}$$

- Pick the  $q^*$  where the two indifference curves cross
  - For any  $q > q^*$

$$t(q,\theta_2) - t(q,\theta_1) = \int_{q^*}^q \frac{\partial U(q,\theta_2)}{\partial q} d(q) - \int_{q^*}^q \frac{\partial U(q,\theta_1)}{\partial q} d(q) + t(q^*,\theta_2) - t(q^*,\theta_1) = \int_{q^*}^q \frac{\partial U(q,\theta_2)}{\partial q} - \frac{\partial U(q,\theta_1)}{\partial q} d(q) > 0$$

• Spence-Mirrlees condition is sometimes called a Sorting condition

#### Theorem

 $q: [\theta_1, \theta_2] \to \mathbb{R}$  belongs to a direct truthful mechanism *if* and only if it is non-decreasing

• Meaning: for any non-decreasing q we can find a t function that makes it part of a truth telling mechanism

- Proof
  - Start with

$$\frac{\partial V}{\partial \hat{\theta}}(\theta, \hat{\theta}) = \frac{\partial U(q(\hat{\theta}), \theta)}{\partial q} q'\left(\hat{\theta}\right) - t'(\hat{\theta})$$

• At the optimum for type  $\hat{\theta}$  we know from IC1

$$t'(\hat{\theta}) = \frac{\partial U(q(\hat{\theta}), \hat{\theta})}{\partial q} q' \left(\hat{\theta}\right)$$

• And so

$$\frac{\partial V}{\partial \hat{\theta}}(\theta, \hat{\theta}) = \left[\frac{\partial U(q(\hat{\theta}), \theta)}{\partial q} - \frac{\partial U(q(\hat{\theta}), \hat{\theta})}{\partial q}\right] q'\left(\hat{\theta}\right)$$

• Stare at

$$\frac{\partial V}{\partial \hat{\theta}}(\theta, \hat{\theta}) = \left[\frac{\partial U(q(\hat{\theta}), \theta)}{\partial q} - \frac{\partial U(q(\hat{\theta}), \hat{\theta})}{\partial q}\right] q'\left(\hat{\theta}\right)$$

 $\bullet\,$  And recall that

$$f(x) = f(\hat{x}) + f'(x^*)(x - \hat{x})$$

for  $x^* \in (x, \hat{x})$ 

• And so

$$\frac{\partial V}{\partial \hat{\theta}}(\theta, \hat{\theta}) = \left[\frac{\partial^2 U(q(\hat{\theta}), \theta^*)}{\partial q \partial \theta} \left(\theta - \hat{\theta}\right)\right] q'\left(\hat{\theta}\right)$$

- Given the Spence-Mirrlees condition, this will have the same sign as  $\left(\theta \hat{\theta}\right)$  as long as  $q\left(\hat{\theta}\right)$  is non-decreasing
- Implies  $V(\theta, \hat{\theta})$ 
  - is increasing in  $\hat{\theta}$  for  $\hat{\theta} < \theta$
  - is decreasing in  $\hat{\theta}$  for  $\hat{\theta} > \theta$
- Global maximizer at  $\hat{\theta} = \theta$

- This is extremely useful
  - Started off with a huge number of global IC conditions
- Turns out we can concentrate on a couple of local conditions
- IC2: implies that q is non-decreasing
- IC1: gives us t from

$$t'(\hat{ heta}) = rac{\partial U(q(\hat{ heta}), heta)}{\partial q}q'\left(\hat{ heta}
ight)$$

• Problem boils down to picking non-decreasing function q (and associated t) that maximizes profit

## Solving the Model

• Assume that the principal gets profit of the following type

t - C(q)

• And that agents satisfy

$$\frac{\partial U}{\partial \theta}(q,\theta) > 0$$
$$\frac{\partial^2 U(q(\hat{\theta}),\theta)}{\partial q \partial \theta} > 0$$

## Solving the Model

• Define

$$v(\theta) = V(\theta, \theta) = u(q(\theta), \theta) - t(\theta)$$

As the information rent that agent of type

• The derivative of this is

$$v'(\theta) = \frac{\partial u(q(\theta), \theta)}{\partial q} q'(\theta) - t'(\theta) + \frac{\partial u(q(\theta), \theta)}{\partial \theta}$$
$$= \frac{\partial u(q(\theta), \theta)}{\partial \theta}$$

• (note that this is the derivative of u wrt 2nd argument)

- By IC 1
- By assumption, this is greater than 0
  - Higher types get higher information rents

## Solving the Model

• Assume (for now) that IR constraints are the same for all types

 $v(\theta) \ge 0$ 

• Or, by the above result

 $v(\theta_1) = 0$ 

• IR of the lowest type is the only one that binds

## Fundamental Theorem of Calculus

• Generally we know

$$f(x) = \int_{x_1}^x f'(y)d(y) + f(x_1)$$

• So we can rewrite

$$v(\theta) = \int_{\theta_1}^{\theta} v'(\tau) d\tau + v(\theta_1)$$
$$= \int_{\theta_1}^{\theta} \frac{\partial u(q(\tau), \tau)}{\partial \theta} d(\tau)$$

• And pin down transfers as

$$t(\theta) = u(q(\theta), \theta) - v(\theta)$$
  
=  $u(q(\theta), \theta) - \int_{\theta_1}^{\theta} \frac{\partial u(q(\tau), \tau)}{\partial \theta} d(\tau)$ 

## The Principal's Objective

• The Principal wants to maximize expected profit

$$\int_{\theta_1}^{\theta_2} \left( t(\theta) - C(q(\theta)) f(\theta) d\theta \right)$$

• Substituting in gives

$$\int_{\theta_1}^{\theta_2} \left( u(q(\theta), \theta) - \int_{\theta_1}^{\theta} \frac{\partial u(q(\tau), \tau)}{\partial \theta} d(\tau) - C(q(\theta)) \right) f(\theta) d\theta$$

• Leaving us with a double integral (eek!)

### Integration by Parts

• We can make more progress by integrating by parts

$$\begin{split} G(\theta) &= \int_{\theta_1}^{\theta} \frac{\partial u(q(\tau), \tau)}{\partial \theta} d(\tau) \\ \Rightarrow &\int_{\theta_1}^{\theta_2} G(\theta) f(\theta) d(\theta) \\ &= [G(\theta)F(\theta)]_{\theta_1}^{\theta_2} - \int_{\theta_1}^{\theta_2} G'(\theta)F(\theta) d(\theta) \\ &= G(\theta_2) - \int_{\theta_1}^{\theta_2} G'(\theta)F(\theta) d(\theta) \\ &= \int_{\theta_1}^{\theta_2} \frac{\partial u(q(\theta), \theta)}{\partial \theta} d(\theta) - \int_{\theta_1}^{\theta_2} \frac{\partial u(q(\theta), \theta)}{\partial \theta} F(\theta) d(\theta) \\ &= \int_{\theta_1}^{\theta_2} \frac{\partial u(q(\theta), \theta)}{\partial \theta} (1 - F(\theta)) d(\theta) \end{split}$$

### Rewriting the Principal's Problem

• And so we can write the Principal's objective as

$$\begin{split} & \int_{\theta_1}^{\theta_2} \left( u(q(\theta), \theta) - \int_{\theta_1}^{\theta} \frac{\partial u(q(\tau), \tau)}{\partial \theta} d(\tau) - C(q(\theta)) \right) f(\theta) d\theta \\ = & \int_{\theta_1}^{\theta_2} H(q(\theta), \theta) f(\theta) d\theta \end{split}$$

• Where

$$H(q,\theta) = u(q,\theta) - C(q) - \frac{\partial u(q,\theta)}{\partial \theta} \frac{1}{h(\theta)}$$

and

$$h(\theta) = \frac{f(\theta)}{1 - F(\theta)}$$

- is the hazard rate
  - Prob of being type  $\theta$  given at least type  $\theta$

### Rewriting the Principal's Problem

$$H(q,\theta) = u(q,\theta) - c(q) - \frac{\partial u(q,\theta)}{\partial \theta} \frac{1}{h(\theta)}$$

- This is the virtual surplus
  - First part is total surplus
  - Second part is the distortion necessary for the IC constraint to hold

### Solving the Problem

$$H(q, \theta) = u(q, \theta) - C(q) - \frac{\partial u(q, \theta)}{\partial \theta} \frac{1}{h(\theta)}$$

- How do we proceed?
- Well, we can start by picking q to maximize H for every  $\theta$ .
- Will this necessarily be the solution?
- No, because the second order IC constrains may not hold
- i.e. it does not guarantee

$$q'(\theta) \ge 0$$

• Cross our fingers and assume it works

## First Order Conditions (again!)

$$H_q(q,\theta) = 0$$
  
$$\Rightarrow u_q(q,\theta) - C'(q) - \frac{\partial^2 u(q,\theta)}{\partial \theta \partial q} \frac{1}{h(\theta)}$$

- Define  $q^*(\theta)$  as the solution to this equation
- If this function is non-decreasing then we are done!
  - Perfect separation
  - Perfect revelation
- Can guarantee this with auxiliary assumptions, e.g
  - $u(q, \theta) = q\theta$
  - $\bullet~C~{\rm convex}$
  - Hazard rate non-decreasing

## **Bunching Solutions**

- If  $q^*(\theta)$  is decreasing for some portion, it cannot be the solution
- We can divide the optimal function into two types of region on the type space
  - q is increasing  $\Rightarrow H_q(q, \theta) = 0$  and  $q(\theta) = q^*(\theta)$
  - $q(\theta)$  is constant

