# Redistribution Mechanisms for Assignment of Heterogeneous Objects

Sujit Prakash Gujar

14 January 2016



- Motivation
  - Examples
  - Quick Recap of Mechanism Design

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  - Introduction
  - State of the Art and Research Gaps
  - Problem Statement

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  - State of the Art and Research Gaps
  - Problem Statement
- Contributions
- Summary and Directions for Future Work

Motivation Quick Introduction to Mechanism Design

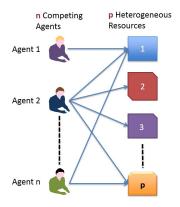
#### Motivating Example



Motivation Quick Introduction to Mechanism Design

### Assignment of Resources in Social Welfare Settings

#### Assignment of *p* resources among *n* of its users



- Telecom Regulatory Authority wishes to allot spectrum licenses
- A university wants to allot real estate to departments
- Assignment should be such that social welfare is maximized

Image: Image:

Motivation Quick Introduction to Mechanism Design

#### Need for Mechanism Design

• Critical need: True valuations to be reported by the agents

Mechanism Design Framework is natural

- Mechanism Design is an important tool in microeconomics
- Mechanisms used in the current context are called **Redistribution** Mechanisms
  - Redistribution Mechanisms: Guo and Conitzer, "Worst Case Optimal Redistribution of VCG Payments", (ACM EC'07),
  - H Moulin, "Efficient, strategy-proof and almost budget-balanced assignment", Journal of Economic theory, 2009

Motivation Quick Introduction to Mechanism Design

# Mechanism Design (MD)

Given:

- a) a set of strategic (utility maximizing) agents with private information,
- b) a social choice function that captures desirable (social) properties

MD provides a game theoretic framework to explore if the given social choice function may be implemented as an equilibrium outcome of an induced game.

Motivation Quick Introduction to Mechanism Design

#### Gibbard-Satterthwaite Impossibility Theorem

#### Theorem

#### lf

- **1** The outcome set X is such that,  $3 \le |X| < \infty$
- 2  $\Re_i = \mathscr{S} \forall i$
- **(**)  $f(\Theta) = X$ , that is, the image of SCF  $f(\cdot)$  is the set X.

then the social choice function SCF  $f(\cdot)$  is truthfully implementable in dominant strategies if and only if it is dictatorial.

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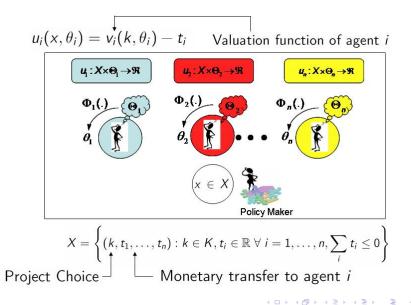
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# **Quasi Linear Environment**

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#### Properties of Mechanisms

Non-Dictatorship

No single agent is favored all the time

Dominant Strategy Incentive Compatibility (DSIC)

**DSIC** Reporting truth is dominant strategy

#### AE

Allocative Efficiency Allocate item to those who value them most

#### IR

Individual Rationality Agents participate voluntarily. (No losses)

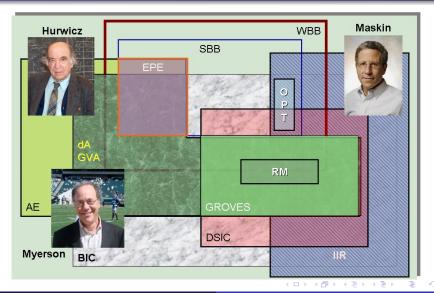
#### SBB

Strict Budget Balance Net transfer of money is zero

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Motivation Quick Introduction to Mechanism Design

# Space of Mechanisms in Quasi-Linear Settings



Introduction
Redistribution Mechanisms
Our Results
Summary
State of the Art
Worst Case Optimal Redistribution Mechanism
Research Gaps

# **Redistribution Mechanisms**

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#### Groves Mechanism

Recall Groves Theorem:

Theorem (Groves Theorem)

An allocatively efficient SCF f can be truthfully implemented in dominant strategies if,

$$t_i(\theta) = -\left[\sum_{j \neq i} v_j(k^*(\theta), \theta_j)\right] + h_i(\theta_{-i}); \quad i = 1, 2, \dots, n$$
 (1)

where  $h_i(\cdot)$  is any arbitrary function of  $\theta_{-i}$ .

<sup>1</sup>T. Groves. Incentives in teams. *Econometrica*, 41:617-631, 1973  $\leftarrow \equiv + + \equiv +$ 

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The above payment is Groves payment scheme. <sup>1</sup>

<sup>&</sup>lt;sup>1</sup>T. Groves. Incentives in teams. *Econometrica*, 41:617-631, 1973 < ≥ → < ≥ → Suit Prakash Gujar. 14 January 2016

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#### Clarke's Mechanism

• In Groves Mechanism, let

$$h_i(\theta_{-i}) = \sum_{j \neq i} v_j(k_{-i}^*(\theta_{-i}), \theta_j); \quad \forall \ \theta_{-i} \in \Theta_{-i}, \ i = 1, \dots, n$$
(2)

• That is, each agent *i* pays,

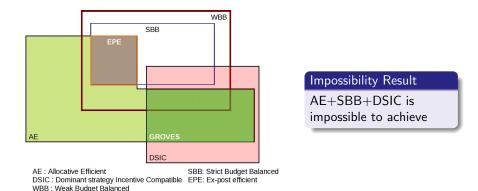
$$t_i(\theta) = -\left[\sum_{j \neq i} v_j(k^*(\theta), \theta_j)\right] + \left[\sum_{j \neq i} v_j(k^*_{-i}(\theta_{-i}), \theta_j)\right]$$
(3)

• This mechanism is called VCG or Clarke's<sup>2</sup> Pivotal Mechanism

<sup>&</sup>lt;sup>2</sup>E. Clarke. Multi-part pricing of public goods. *Public Choice*, 11:17-23, 1971 =  $\circ$  Q

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## Green Laffont Impossibility Theorem



J. R. Green and J. J. Laffont, "Incentives in Public Decision Making". North-Holland Publishing Company, Amsterdam, 1979

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#### Two Approaches to Design Mechanisms



- Approximate AE
  - Faltings [1]: Randomly select pool of agents who collect all the revenue
  - Guo and Conitzer [2]: Burn certain number of items
- Today's Talk: Reduce Budget Imbalance
  - Redistribution Mechanisms

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#### Redistribution Mechanism

• Laffont and Maskin [3] <sup>3</sup> : redistribute the surplus

<sup>3</sup>J.J. Laffont and E. Maskin. A differential approach to expected utility maximizing mechanisms. In J. J Laffont, editor, Aggregation and Revelation of Preferences. 1979.

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- Redistribute the surplus that preserves AE and DSIC (Design Appropriate Groves mechanism)

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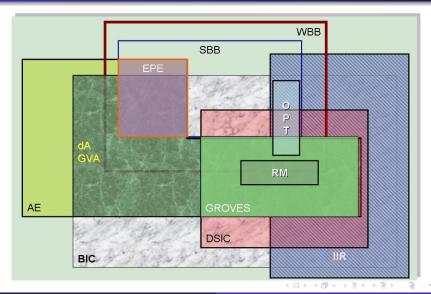
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- Collect VCG payments, and redistribute equally among the participating agents
  - $\times$  Not Incentive Compatible
- Redistribute the surplus that preserves AE and DSIC (Design Appropriate Groves mechanism)
- Refer to it as redistribution mechanism

<sup>3</sup>J.J. Laffont and E. Maskin. A differential approach to expected utility maximizing mechanisms. In J. J Laffont, editor, Aggregation and Revelation of Preferences. 1979.

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# RM in Space of Mechanisms



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#### Redistribution Mechanisms

- Groves mechanism: design payment functions  $h_i(\theta_{-i})$ s for all the agents.
- VCG mechanism:  $h_i(\theta_{-i}) = \sum_{j \neq i} v_j(k_{-i}^*(\theta_{-i}), \theta_j)$
- Let  $h_i(\theta_{-i}) = \sum_{j \neq i} v_j(k_{-i}^*(\theta_{-i}), \theta_j) r_i(\theta_{-i})$ where,  $r_i(.)$  is rebate function for the agent *i*.
- A redistribution mechanism: involves designing an appropriate rebate function

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State of the Art Worst Case Optimal Redistribution Mechanism Research Gaps

#### State of the Art and Research Gaps

All the previous work assumes the objects are identical (Homogeneous settings).

• Cavallo [4]<sup>4</sup> : rebate function that depends only on (*p* + 2) highest bids

<sup>4</sup>This scheme can be viewed as Bailey [5] scheme applied in the setting  $\langle \cdot \rangle$ 

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$$L(n, p) = \max_{\theta \in \Theta} \frac{\text{Budget Surplus} = \sum_{i} t_{i} - r_{i}}{\text{Efficient Surplus} = \sum_{i} v_{i}(k^{*}, .)}$$

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• Guo and Conitzer [7] : performance ratio of a mechanism as,

$$\min_{\theta \in \Theta} \frac{\text{Surplus redistributed} = \sum_{i} r_i}{\text{VCG Surplus} = \sum_{i} t_i}$$

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• Guo and Conitzer [8] : mechanism which is optimal in expected sense

<sup>4</sup>This scheme can be viewed as Bailey [5] scheme applied in the setting  $\langle \Xi \rangle = 2$ 

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#### Bailey-Cavello Mechanism

- Sort the received bids
- The highest *p* bidders get the objects
- The winners pay VCG payment:  $p + 1^{st}$  bid
- Rebate r<sub>i</sub>() to i<sup>th</sup> agent

$$r_i = \frac{1}{n} v_{p+2} \text{ if } i = 1, 2, \dots, p+1$$
  
=  $\frac{1}{n} v_{p+1} \text{ if } i = p+2, p+3, \dots, n$ 

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#### WCO Mechanism

Moulin [6] and Guo and Conitzer [7] : Worst Case Optimal (WCO) Mechanism,

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$$r_i = f(\theta_1, \theta_2, \dots, \theta_{i-1}, \theta_{i+1}, \dots, \theta_n)$$
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(4)

where,

$$f(x_1, x_2, \dots, x_{n-1}) = \sum_{\substack{j=p+1 \\ j=p+1}}^{n-1} c_j x_j$$
$$c_i = \frac{(-1)^{i+p-1} (n-p) \binom{n-1}{p-1}}{i \binom{n-1}{i} \sum_{\substack{j=p \\ j=p}}^{n-1} \binom{n-1}{j}} \left\{ \sum_{\substack{j=i \\ j=i}}^{n-1} \binom{n-1}{j} \right\}; \ i = p+1, \dots, n-1$$

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# An Example of WCO Mechanism

Consider: p = 1 and n = 3.

VCG Mechanism

The highest bidder will win and pay the second highest bid

• WCO Mechanism

Say,  $v_1 \ge v_2 \ge v_3$ 

$$\begin{array}{rcl}
p_1 &=& v_2 - \frac{1}{3}v_3 \\
p_2 &=& -\frac{1}{3}v_3 \\
p_3 &=& -\frac{1}{3}v_2 \\
e &=& \frac{1}{3}
\end{array}$$
(5)

Say 
$$v_1 = 1, v_2 = 1, v_3 = 0$$
  
 $t_1 = -1, t_2 = 0, t_3 = 0, p_1 = -1, p_2 = 0p_3 = \frac{1}{3}$   
 $e = \frac{\frac{1}{3}}{1} = \frac{1}{3}$ 

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### Problem We Are Addressing

- *p* heterogeneous objects to be assigned among *n* competing agents, where *n* > *p* and agents have unit demand
- All the previous work assumes objects are homogeneous

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# Problem We Are Addressing

- *p* heterogeneous objects to be assigned among *n* competing agents, where *n* > *p* and agents have unit demand
- All the previous work assumes objects are homogeneous

#### Goal

Design a **redistribution mechanism** which is individually rational, feasible and worst case optimal for assignment of p heterogeneous objects among n agents with unit demand.

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# **Problem Formulation**

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# **Problem Formulation**

Goal:

$$\begin{array}{rcl}
m^{*} &= \arg \max_{m \in \mathscr{M}} e(m) \\ & \text{s.t.} \\
r_{i}(.) &\geq 0, \forall \ \theta \in \Theta \ \forall i \in \mathbb{N} \quad \text{Individual Rationality} \\
\sum_{i} r_{i}(.) &\leq t \quad & \text{Feasibility}
\end{array}$$
(6)

• Linear rebate function: rebate function for an agent *i* is linear combination of bids of remaining (n-1) agents

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### **Our Contributions**

- Impossibility of linear rebate functions with non-zero redistribution index
- Possibility of such functions in restricted settings
- Existence of non-linear rebate function that has non-zero efficiency
- HETERO, a non-linear rebate function

• It satisfies desired properties and is optimal on worst case analysis Sujit Gujar and Y Narahari, "Redistribution Mechanisms for Assignment of Heterogeneous Objects". Journal of Artificial Intelligence Research (JAIR), 2011, Volume 41, pp: 131-154.

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# Impossibility of Linear Rebate Scheme

 $\mathcal{M}_L$ : Space of anonymous redistribution mechanisms in which rebate functions are linear.

Problem reduces to,

$$\begin{array}{rcl}
m^{*} &= \arg \max_{m \in \mathscr{M}_{L}} e(m) \\ & \text{s.t.} \\
r_{i}(.) \geq 0, \forall \theta \in \Theta \forall i \in N \\
\sum_{i} r_{i}(.) \leq t
\end{array}$$
(7)

Image: Image:

• For this setting, we prove,  $e(m^*) = 0$ 



#### Theorem

If a mechanism has to be feasible and individually rational, there **does not exist** a **linear** rebate function which satisfies all the following properties,

DSIC

• deterministic

anonymous

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• guarantees non-zero redistribution in worst case

[?] "Redistribution Mechanisms for Assignment of Heterogeneous Objects", Sujit Gujar and Y Narahari, *Journal of Artificial Intelligence Research, (JAIR), Vol 41, 131-154 (2011)*.

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#### Sketch of the Proof

Step1 Define Ordering of the agents based on bids (≽)
Step2 We prove,

#### Theorem

Any deterministic, anonymous rebate function f is DSIC iff,

$$r_i = f(v_1, v_2, \dots, v_{i-1}, v_{i+1}, \dots, v_n) \ \forall i \in N$$
 (8)

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where,  $v_1 \succcurlyeq v_2 \succcurlyeq \ldots \succcurlyeq v_n$ .

#### Step3

$$\begin{aligned} r_i &= f(v_1, v_2, \dots, v_{i-1}, v_{i+1}, \dots, v_n) \\ &= (c_0, e_p) + (c_1, v_1) + \dots + (c_{n-1}, v_n) \end{aligned}$$

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# Sketch of the Proof of Theorem Continued

- Step 4 Show that,  $c_0, c_1, \ldots, c_{p+1} = 0$
- Step 5 Construct type profile such that, VCG Payment is non zero. However, the rebate to each of the agents is zero.

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#### How do we get around this impossibility result?

Route 1 Restrict the domain of types

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# Sketch of the Proof of Theorem Continued

- Step 4 Show that,  $c_0, c_1, ..., c_{p+1} = 0$
- Step 5 Construct type profile such that, VCG Payment is non zero. However, the rebate to each of the agents is zero.

#### How do we get around this impossibility result?

- Route 1 Restrict the domain of types
- Route 2 Explore non-linear rebate functions

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# Route 1: Restrict the Domain of Types

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# Restrict the Domain of Types: An Example of Scaling Based Valuation

Motivation:

- Consider the website somefreeads.com
- There are *p* slots available for advertisements, and *n* agents interested in displaying their ads

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# Restrict the Domain of Types: An Example of Scaling Based Valuation

Motivation:

- Consider the website somefreeads.com
- There are *p* slots available for advertisements, and *n* agents interested in displaying their ads

#### Definition

We say the valuations of the agents have scaling based relationship if there exist positive real numbers  $\alpha_1, \alpha_2, \alpha_3, \ldots, \alpha_p > 0$  such that, for each agent  $i \in N$ , the valuation for object j, say  $\theta_{ij}$ , is of the form  $\theta_{ij} = \alpha_j v_i$ , where  $v_i \in \mathbb{R}_+$  is a private signal observed by agent i.

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### Proposed Mechanism

- The agents submit their bids.
- The bids are sorted in decreasing order.
- The highest bidder will be allotted the first object, the second highest bidder will be allotted the second object, and so on.
- Agent *i* will pay  $t_i r_i$ , where  $t_i$  is the Clarke payment and  $r_i$  is the rebate.

$$t_i = \sum_{j=i}^{p} (\alpha_j - \alpha_{j+1}) v_{j+1}$$

Impossibility of Linear Rebate Functions Scaling Based Valuation Non-Linear Rebate Functions

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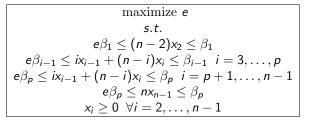
#### Proposed Mechanism

• Let agent *i*'s rebate be,

$$r_i = c_2 v_2 + \ldots + c_{i-1} v_{i-1} + c_i v_{i+1} + \ldots + c_{n-1} v_n$$

• Define 
$$\beta_1 = \alpha_1 - \alpha_2$$
, and for  $i = 2, \dots, p$ , let  $\beta_i = i(\alpha_i - \alpha_{i+1}) + \beta_{i-1}$ .

• Define 
$$x_j = \sum_{i=2}^{j} c_i$$
 for  $j = 2, ..., n - 1$ .



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(9)

The discussion above can be summarized as the following theorem.<sup>5</sup>

#### Theorem

When the valuations of the agents have scaling based relationship, for any p and n > p + 1, the linear redistribution mechanism obtained by solving LP (9) is worst case optimal among all Groves redistribution mechanisms that are feasible, individually rational, deterministic, and anonymous.

<sup>&</sup>lt;sup>5</sup> [?] "Redistribution Mechanisms for Assignment of Heterogeneous Objects", Sujit Gujar and Y Narahari, *Journal of Artificial Intelligence Research, (JAIR), Vol 41,* 131-154 (2011)

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# Route 2: Explore Non-Linear Rebate Functions

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#### **BAILEY** Mechanism

We apply Bailey [5]<sup>6</sup> mechanism to these settings,

$$r_i^B = \frac{1}{n}t^{-i}$$

<sup>6</sup>Martin J Bailey. The demand revealing process: To distribute the surplus. Public Choice, 91(2):107-26, April 1997.

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### **BAILEY** Mechanism

We apply Bailey [5]<sup>6</sup> mechanism to these settings,

$$r_i^B = \frac{1}{n}t^{-1}$$

#### Proposition

The BAILEY redistribution scheme,

- is feasible
- individually rational and
- non-zero fraction of VCG surplus is always redistributed when n > 2p

<sup>6</sup>Martin J Bailey. The demand revealing process: To distribute the surplus. Public Choice, 91(2):107-26, April 1997.

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# HETERO (Our Proposed Mechanism)

•  $t^{-i,k}$ : average payment received when agent *i* is absent along with *k* other agents

<sup>&</sup>lt;sup>7</sup>Sujit Gujar and Y Narahari, "Redistribution of VCG payments in assignment of heterogeneous objects". In Proceedings of 4<sup>th</sup> Workshop on Internet and Network Economics, WINE 2008. pg 438-445.

Impossibility of Linear Rebate Functions Scaling Based Valuation Non-Linear Rebate Functions

# HETERO (Our Proposed Mechanism)

- $t^{-i,k}$ : average payment received when agent *i* is absent along with *k* other agents
- We propose <sup>7</sup>

$$r_i^{\mathsf{H}} = \alpha_1 t^{-i} + \sum_{k=2}^{k=L} \alpha_k t^{-i,k-1}$$
(10)

<sup>&</sup>lt;sup>7</sup>Sujit Gujar and Y Narahari, "Redistribution of VCG payments in assignment of heterogeneous objects". In Proceedings of 4<sup>th</sup> Workshop on Internet and Network Economics, WINE 2008. pg 438-445.

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$$r_i^{\mathsf{H}} = \alpha_1 t^{-i} + \sum_{k=2}^{k=L} \alpha_k t^{-i,k-1}$$
(10)

where, L = n - p - 1 and for  $i = p + 1 \rightarrow n - 1$ 

$$c_{i} = \sum_{k=0}^{n-i-1} \alpha_{L-k} \times \frac{\binom{i-1}{p}\binom{n-i-1}{k}}{\binom{n-1}{p+1+k}}$$
(11)

<sup>7</sup>Sujit Gujar and Y Narahari, "Redistribution of VCG payments in assignment of heterogeneous objects". In Proceedings of  $4^{th}$  Workshop on Internet and Network Economics, WINE 2008. pg 438-445.

Introduction Redistribution Mechanisms Our Results Summary Non-Linear Rebate Functions

•  $\alpha$ 's are given by,

$$\alpha_{i} = \frac{(-1)^{(i+1)}(L-i)!p!}{(n-i)!}\chi \sum_{j=0}^{L-i} \left\{ \begin{pmatrix} i+j-1 \\ j \end{pmatrix} \sum_{l=p+i+j}^{n-1} \begin{pmatrix} n-1 \\ l \end{pmatrix} \right\};$$
  
$$i = 1, 2, \dots, L$$
(12)

where, 
$$\chi$$
 is given by,  $\chi = rac{(n-p) \left( \begin{array}{c} n-1 \\ p-1 \end{array} \right)}{\sum_{j=p}^{n-1} \left( \begin{array}{c} n-1 \\ j \end{array} \right)}$ 

 HETERO agrees with the WCO mechanism when objects are homogeneous

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Impossibility of Linear Rebate Functions Scaling Based Valuation Non-Linear Rebate Functions

# How Does HETERO Works?

#### Our Conjecture

The proposed scheme, HETERO, is individually rational, feasible and worst case optimal.

<sup>&</sup>lt;sup>8</sup>M Guo and V Conitzer, "Worst-case optimal redistribution of VCG payments". In EC'07: Proceedings of the 8<sup>th</sup> ACM conference on Electronic Commerce, EC, pages 30-39, New York, NY, USA, 2007. ACM.

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# How Does HETERO Works?

#### Our Conjecture

The proposed scheme, HETERO, is individually rational, feasible and worst case optimal.

Our Conjecture is based on the result of Guo and Conitzer  $^{\rm 8}$  :

#### Theorem 1

For any 
$$x_1 \ge x_2 \ge \ldots x_n \ge 0$$
,

$$a_1x_1 + a_2x_2 + \ldots a_nx_n \ge 0$$
 iff  $\sum_{i=1}^j a_i \ge 0 \quad \forall j = 1, 2 \ldots, n.$ 

<sup>8</sup>M Guo and V Conitzer, "Worst-case optimal redistribution of VCG payments". In EC'07: Proceedings of the 8<sup>th</sup> ACM conference on Electronic Commerce, EC, pages 30-39, New York, NY, USA, 2007. ACM.

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### How Does HETERO Works?

- Define,  $\Gamma_1 = t^{-i}, \ \Gamma_j = t^{-i,j-1}, \ j = 2, \dots, L$
- Rebate function for agent i,

$$r = \sum_{j} \alpha_{j} \Gamma_{j}$$

$$3 \ \, \mathsf{Note}, \ \, \mathsf{\Gamma}_1 \geq \mathsf{\Gamma}_2 \geq \ldots \geq \mathsf{\Gamma}_L \geq \mathsf{0}$$

- For p = 2, n = 4,5,6; p = 3, n = 5,6,7; individual rationality follows from Theorem 1
- If  $\sum_{i=1}^{j} \alpha_i \ge 0 \ \forall j = 1 \rightarrow L$ , individual rationality would follow from Theorem 1
- $\Gamma_i$ 's are related
- Q a<sub>j</sub>'s give appropriate weights to the combinations when a particular agent is absent in the system along with j 1 agents

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# Experiments and Empirical Evidence

#### Setup 1

- *p* = 2, *n* = 5, 6, ..., 14, # Experiments 200, 000
- p = 3, n = 7, 8, ..., 14, # Experiments 40,000
- $p = 4, n = 9, 10, \dots, 14$ , # Experiments 40,000

HETERO is individually rational, feasible and performs at least as well as worst case optimal mechanism

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HETERO is individually rational, feasible and performs at least as well as worst case optimal mechanism

#### Setup 2

Assume all the agents have binary valuations on each of these objects

• 
$$p = 2, n = 5, 6, \dots, 12$$

Enumerate all possible bids.

HETERO is individually rational, feasible, and worst case optimal

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# **HETERO**

#### Our Conjecture

The proposed scheme, HETERO, is individually rational, worst case optimal.



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Image: Image:

# **HETERO**

#### Our Conjecture

The proposed scheme, HETERO, is individually rational, worst case optimal.

- Guo [9] showed that HETERO is individually rational and worst case optimal for unit demand case.
- [9] also conjectured that it is a worst case optimal for any general combinatorial auctions with gross substitutes

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# HETERO: Proof

- $r_i^H = \sum_{j=p+1}^n \gamma_j R(N,j)$
- R(N,0): VCVG Surplus
- R(N,j) recursive definition in terms of R(N-a,j-1)
- $R(N,0) \ge R(N,1) \ge ... R(N,n-p-1) \ge 0$
- Invoke Theorem 1 to prove IR, Feasibility and Optimalaity of HETERO

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Summary

# We have Seen

- Need to Redistribution Mechanisms
- $\times\,$  No linear rebate function can guarantee non-zero redistribution index for heterogeneous objects case
  - Two ways to get around this
    - Restrict the domain of types
    - Non-linear rebate functions
  - Scaling Based Relationship
  - HETERO,

HETERO agrees with Moulin scheme in case of homogeneous objects

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Summary

# Thank You!!!

Sujit Prakash Gujar

14 January 2016 46

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