

Combinatorial Exchanges

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- What is a combinatorial exchange?
- Two-sided
- Complex valuations (swaps, contingent swaps, all-or-nothing sells, etc.)

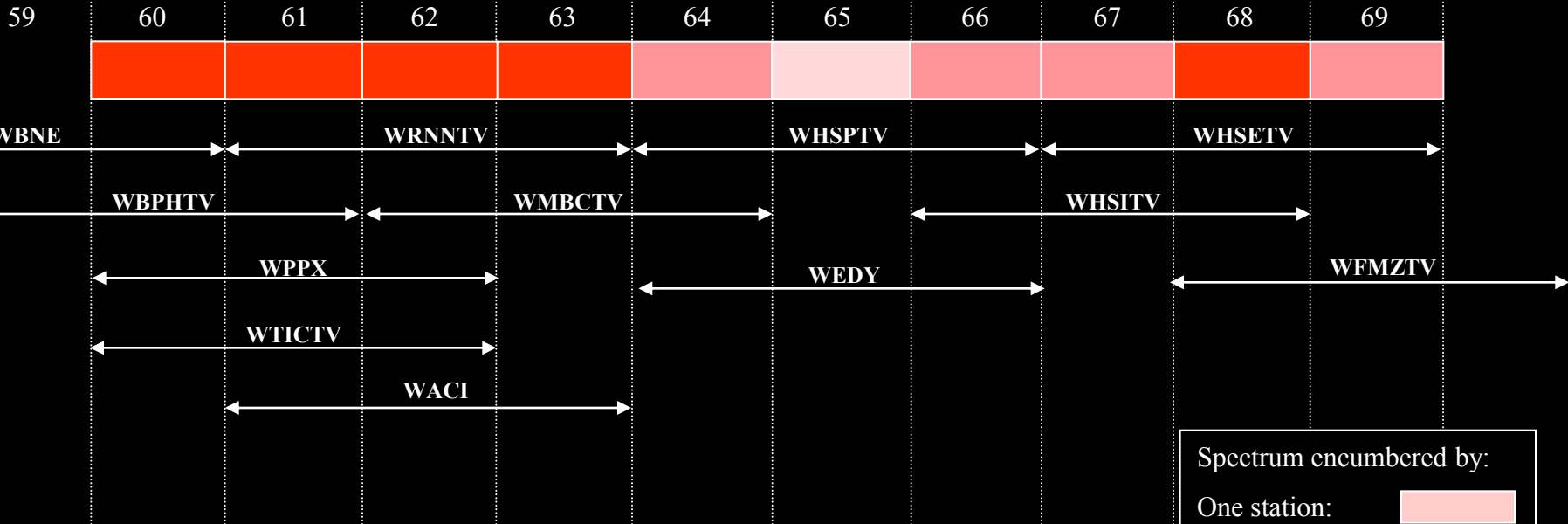
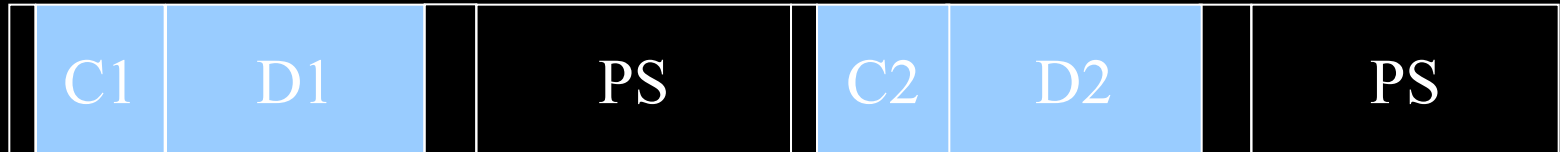
Fragmented Spectrum

(E.Kwerel)

Channel 59-69 TV Incumbents Within 100 Miles of New York City

747 752 762 777 782 792

746 806



Spectrum encumbered by:

One station: 

Two stations: 

Three or more: 

Challenges

- Expressive bidding language
- Preference Elicitation / Price discovery
- Scalable Winner Determination
- Payments:
 - Incentive compatibility
 - Stability
 - Fairness
 - ...

Computational MD

- Economic constraints
 - e.g., incentive compatibility, core, etc.
- Computational constraints
 - e.g., scalable winner determination, minimal preference elicitation, etc.

“Mechanism” = “Algorithm”

Exchange Example

-10

sell A

-5

sell B

+5

swap A for B

exchange

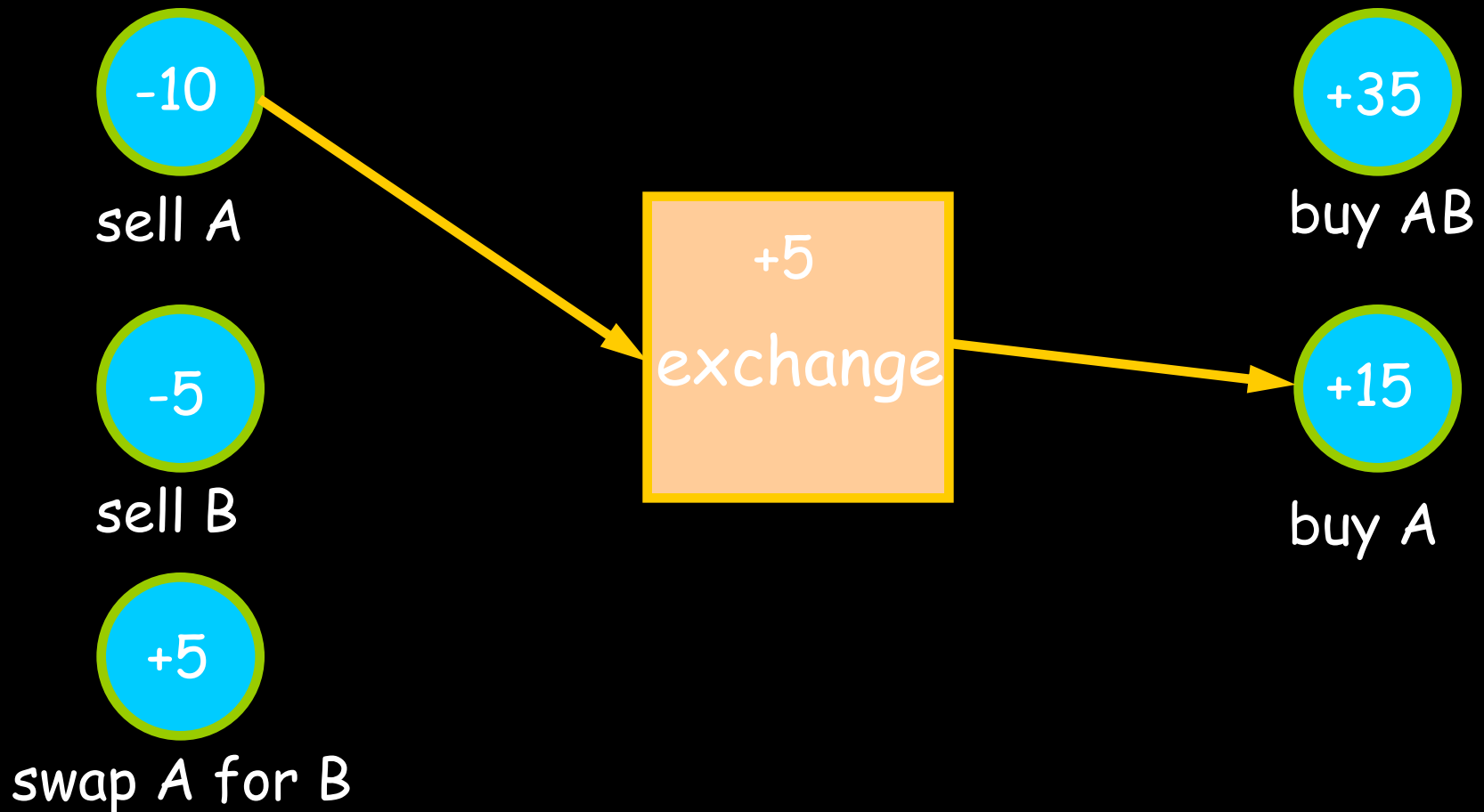
+35

buy AB

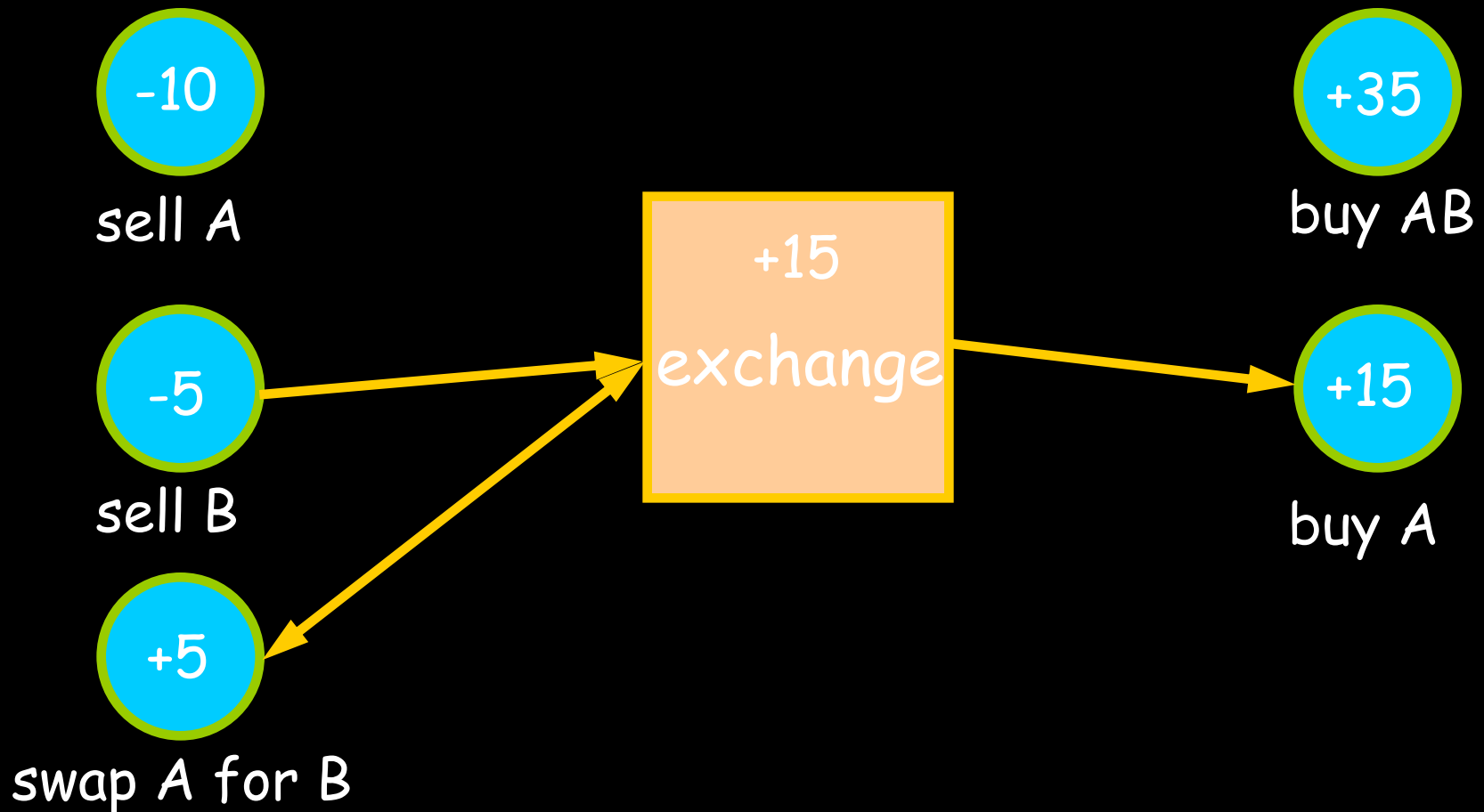
+15

buy A

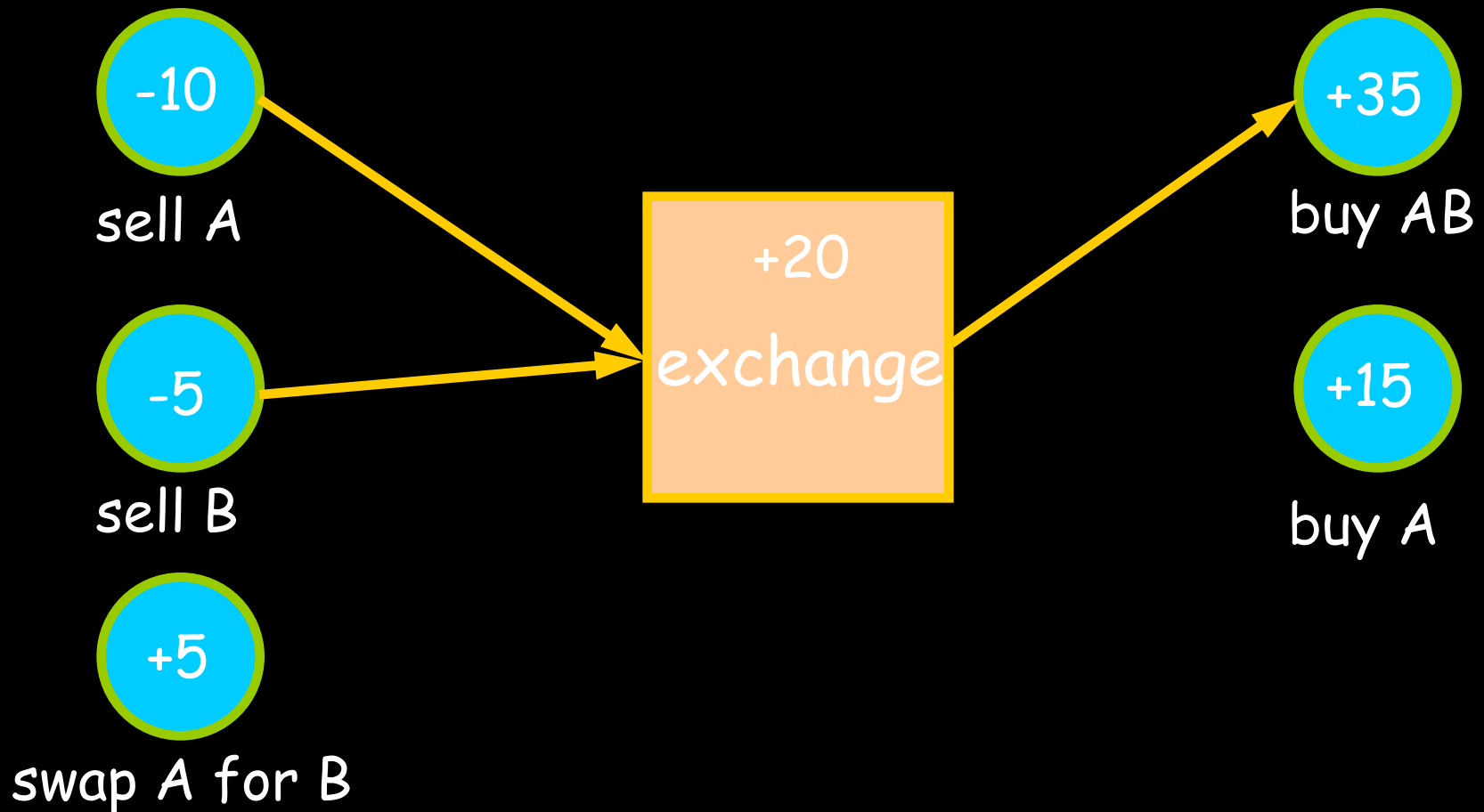
Exchange Example



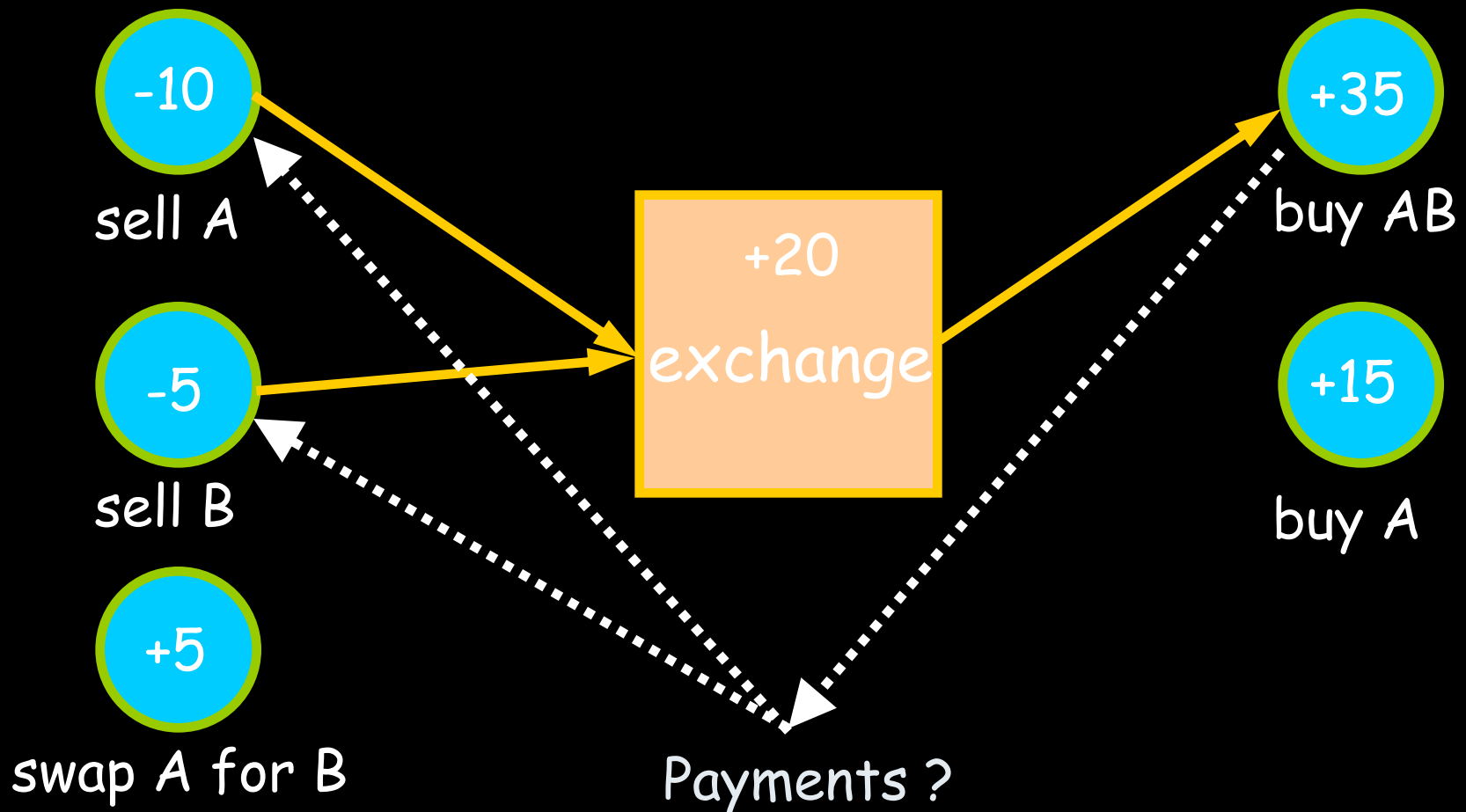
Exchange Example



Exchange Example



Exchange Example



Tree Based Bidding Language

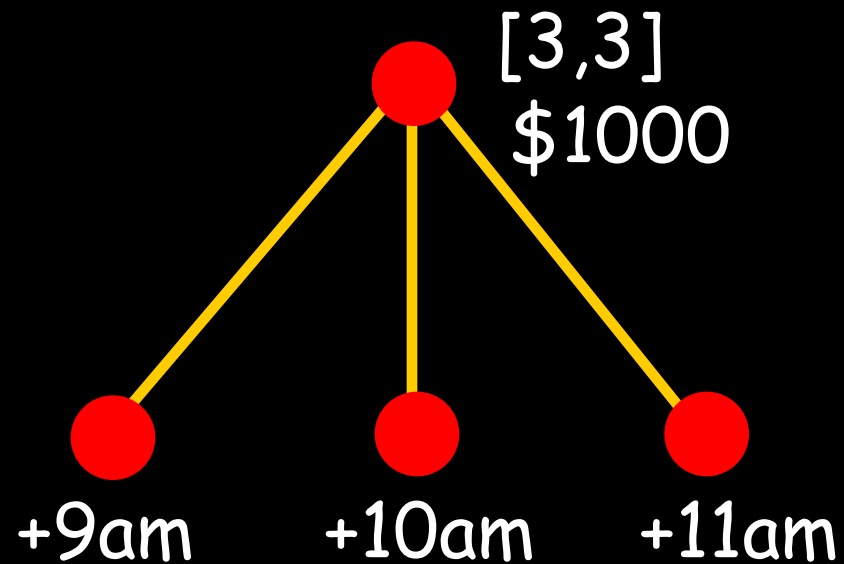
(Cavallo et al.'05)

- Defines change in value for a trade
 - entirely symmetric for buyers and sellers
 - “sell AB, value -\$100”; “buy A, value +\$20”

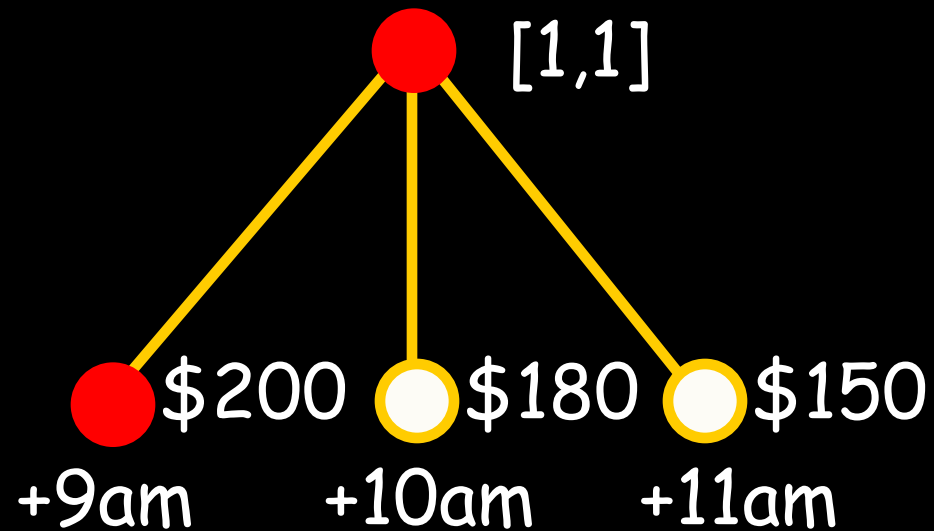
- Generalizes XOR, OR, XOR/OR

(Sandholm'99, Nisan'00)

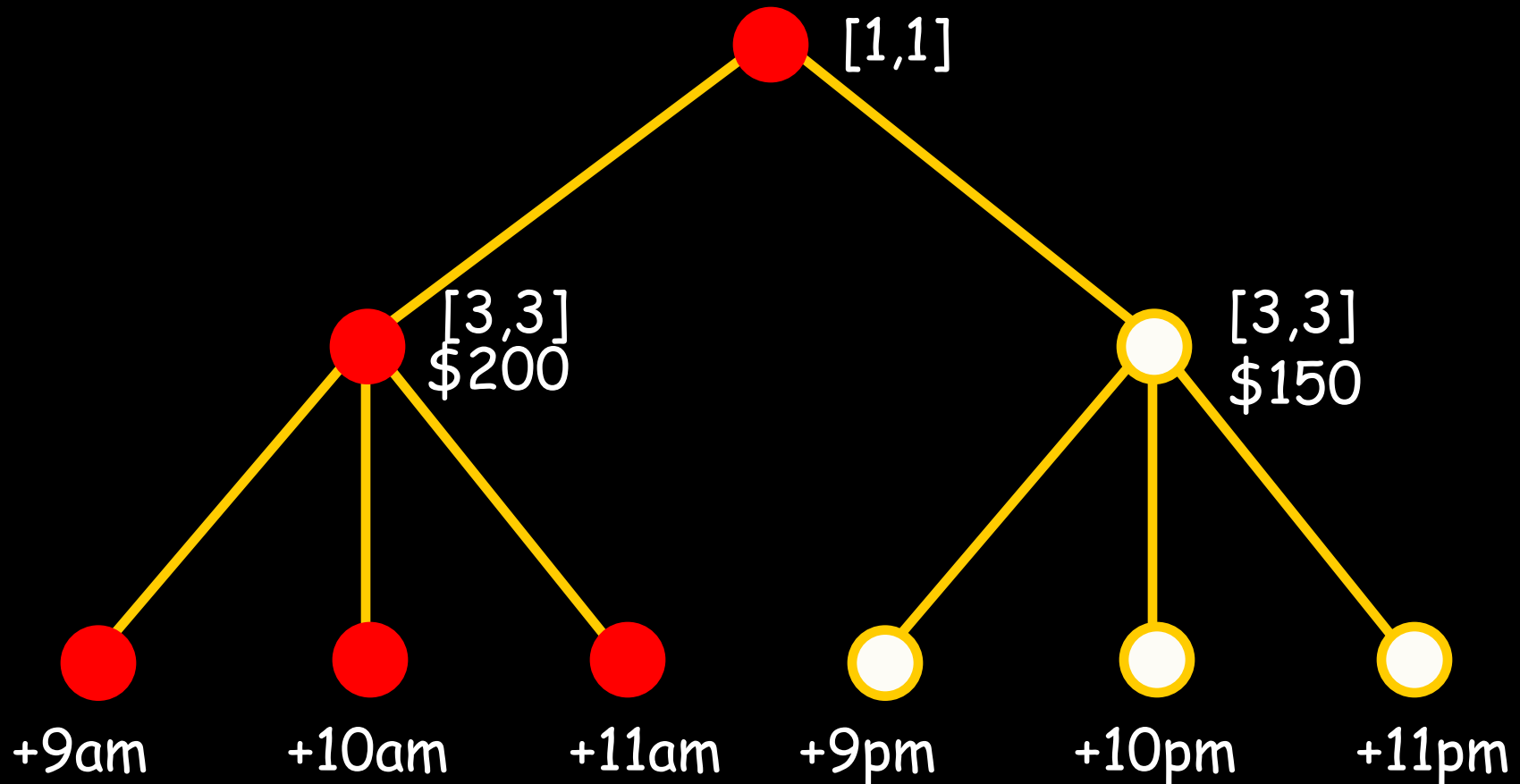
Example 1: “and”



Example 2: “xor”

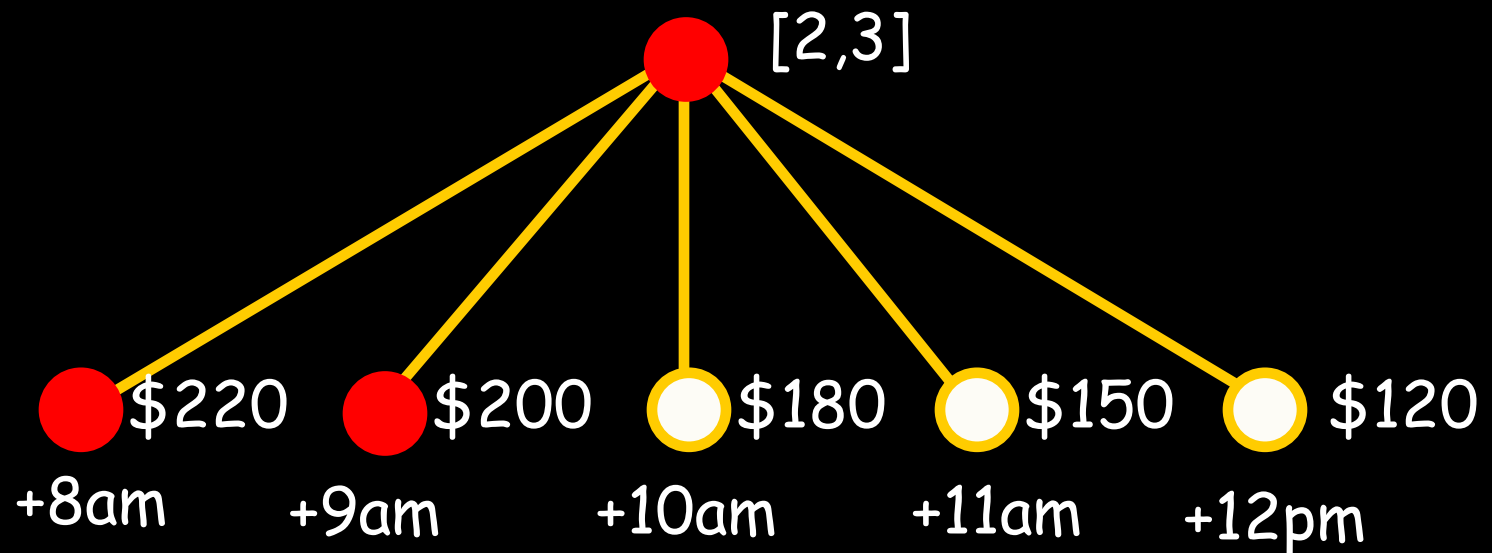


Example 3: “xor of and”

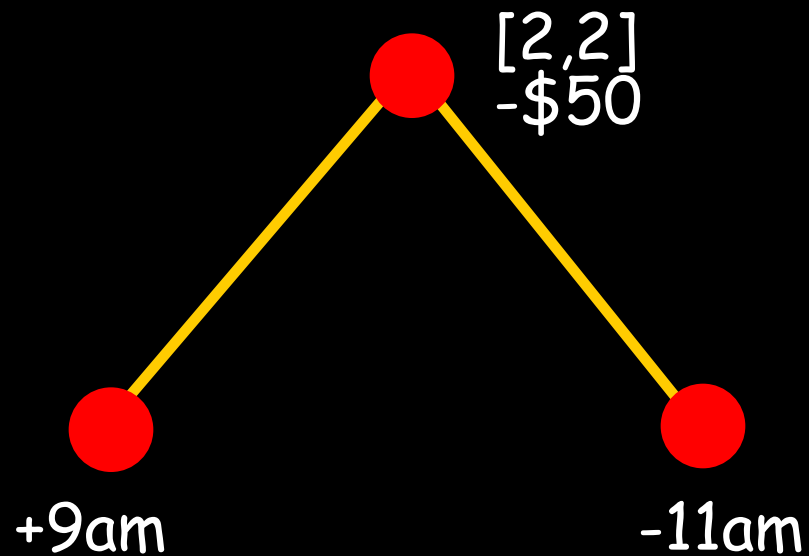


Example 4: “choose”

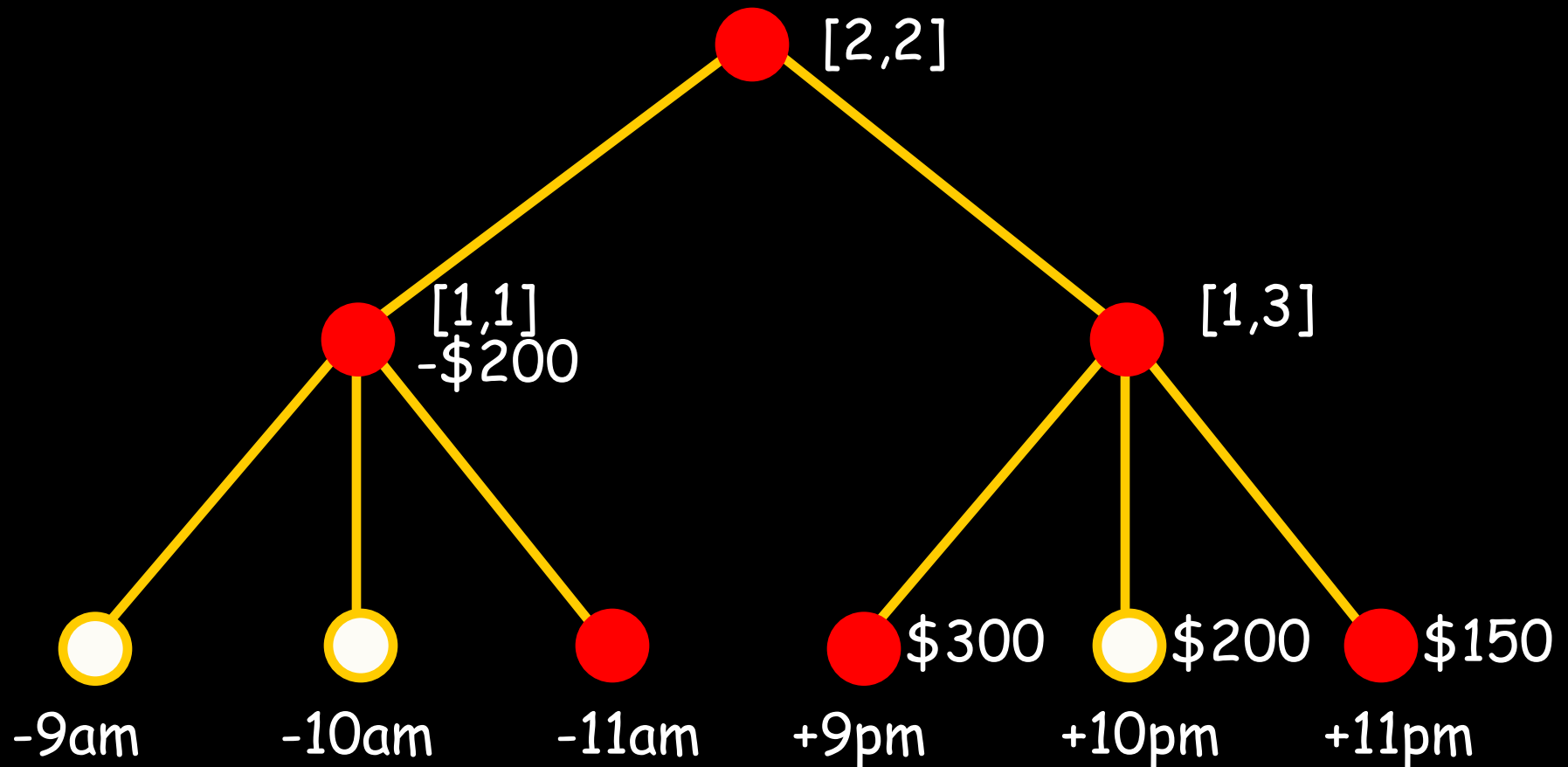
- $IC[x, y]$: accept an allocation in which *at least* x and *at most* y children are “satisfied”



Example 5: “swap”



Example 6: “contingent sale”



Winner Determination

- Goods: $\{1, \dots, m\}$. Agents: $\{1, \dots, n\}$
- Trades: $\lambda_{ij} \in \mathbb{Z}$ Initial allocation: $x^0_{ij} \in \mathbb{Z}$
- Winner determination:

$$\begin{array}{ll}
 \max & \sum_i v_i(\lambda_i) \\
 \text{s.t.} & \lambda_{ij} + x^0_{ij} \geq 0, \quad \forall i \quad \forall j \\
 & \sum_i \lambda_{ij} \leq 0, \quad \forall j \\
 & \lambda_{ij} \in \mathbb{Z}
 \end{array}
 \quad \left. \vphantom{\begin{array}{l} \lambda_{ij} + x^0_{ij} \geq 0, \quad \forall i \quad \forall j \\ \sum_i \lambda_{ij} \leq 0, \quad \forall j \\ \lambda_{ij} \in \mathbb{Z} \end{array}} \right\} \lambda \in \text{feas}(x^0)$$

Value given λ_i ?

$$\begin{aligned} \max_{\text{sat}_i\{\beta\}} \quad & \sum_{\beta \in T} v_i(\beta) \text{sat}_i(\beta) \\ \text{s.t.} \quad & \sum_{\beta \in \text{Leaf}(i)} q_{ij}(\beta) \text{sat}_i(\beta) \leq \lambda_{ij}, \quad \forall j \end{aligned} \quad (3)$$

$$\begin{aligned} \text{IC}_{x,i}(\beta) \text{sat}_i(\beta) &\leq \sum_{\beta' \in \text{child}(\beta)} \text{sat}_i(\beta') \\ &\leq \text{IC}_{y,i}(\beta) \text{sat}_i(\beta), \quad \forall \beta \notin \text{Leaf}(i) \end{aligned} \quad (4)$$

$$\text{sat}_i(\beta) \in \{0, 1\}$$

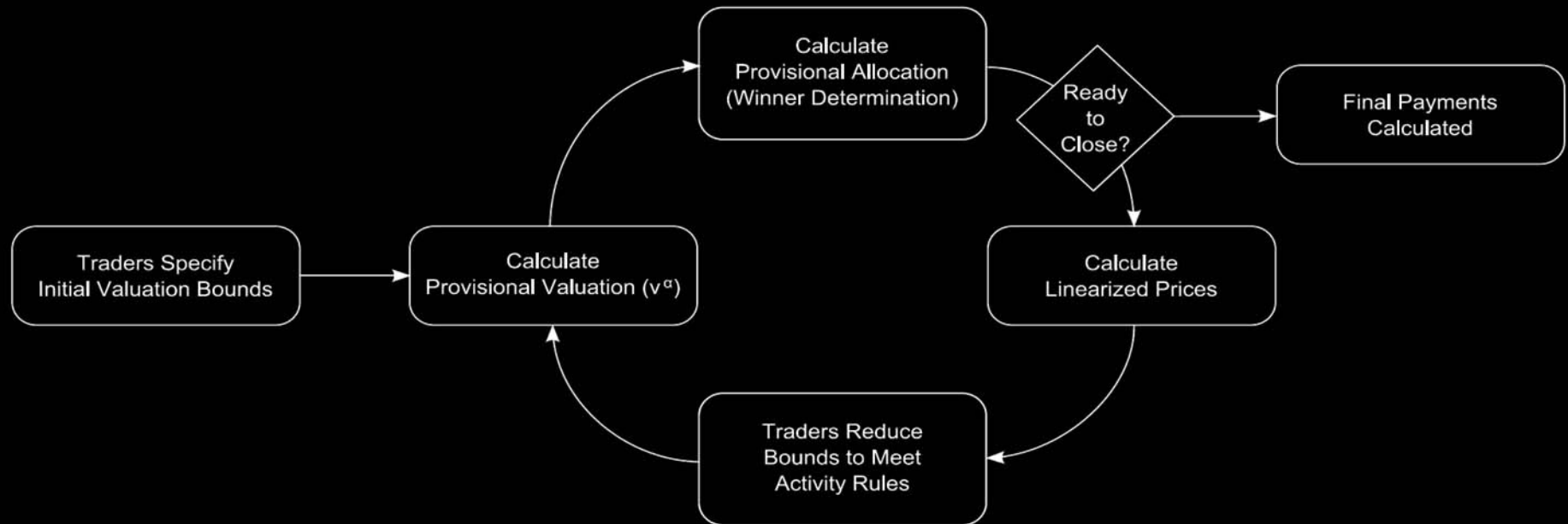
Concise WD Formulation

$$\begin{aligned} \max_{\lambda, \text{sat}} \quad & \sum_i \sum_{\beta \in T_i} v_i(\beta) \text{sat}_i(\beta) \\ \text{s.t.} \quad & (\text{feas}), (\text{TBBL semantics}) \end{aligned}$$

Linear in size of TBBL trees

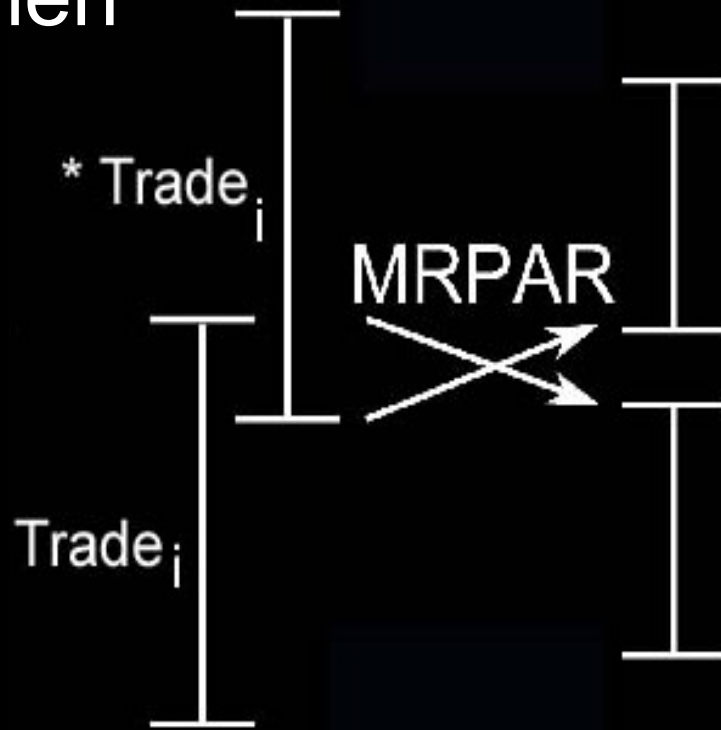
ICE: Proxied Exchange

(Parkes et al. 2007)



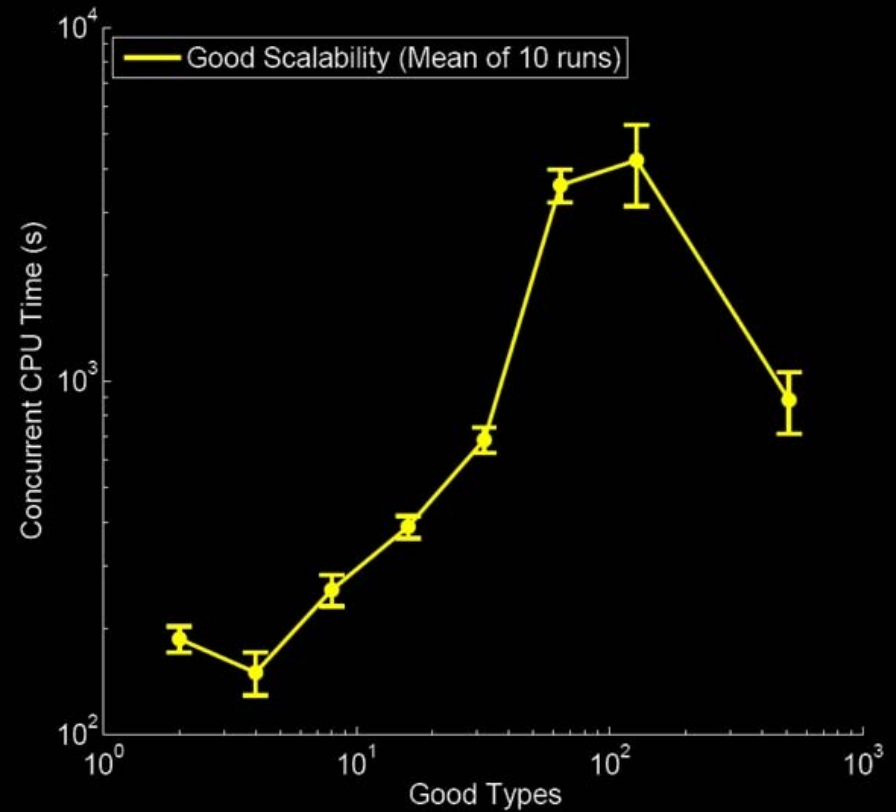
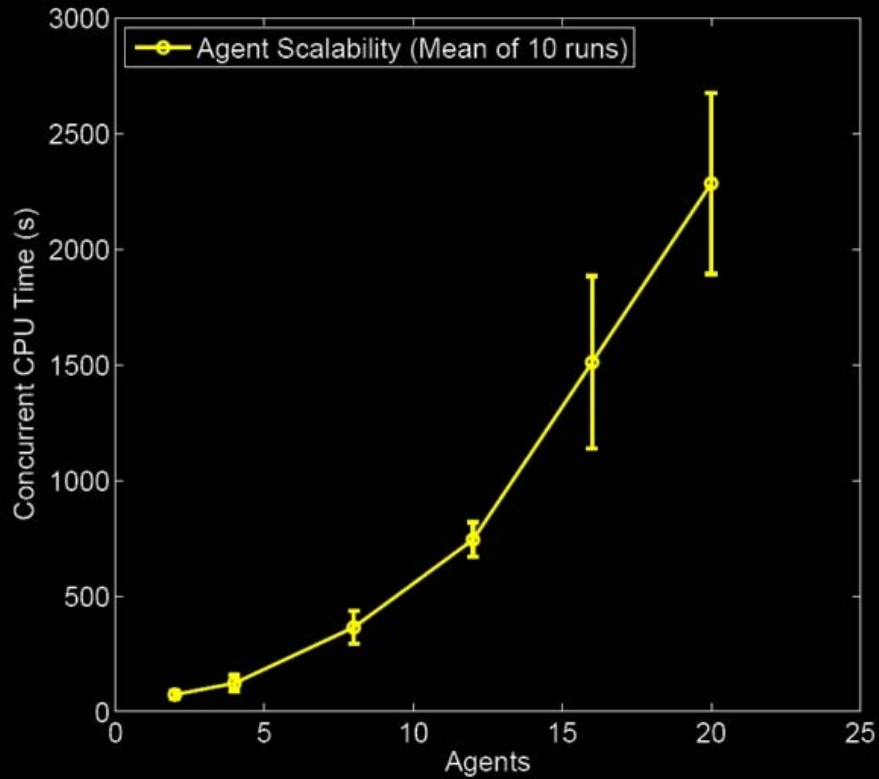
Activity Rule

- Show one trade is weakly better than all others

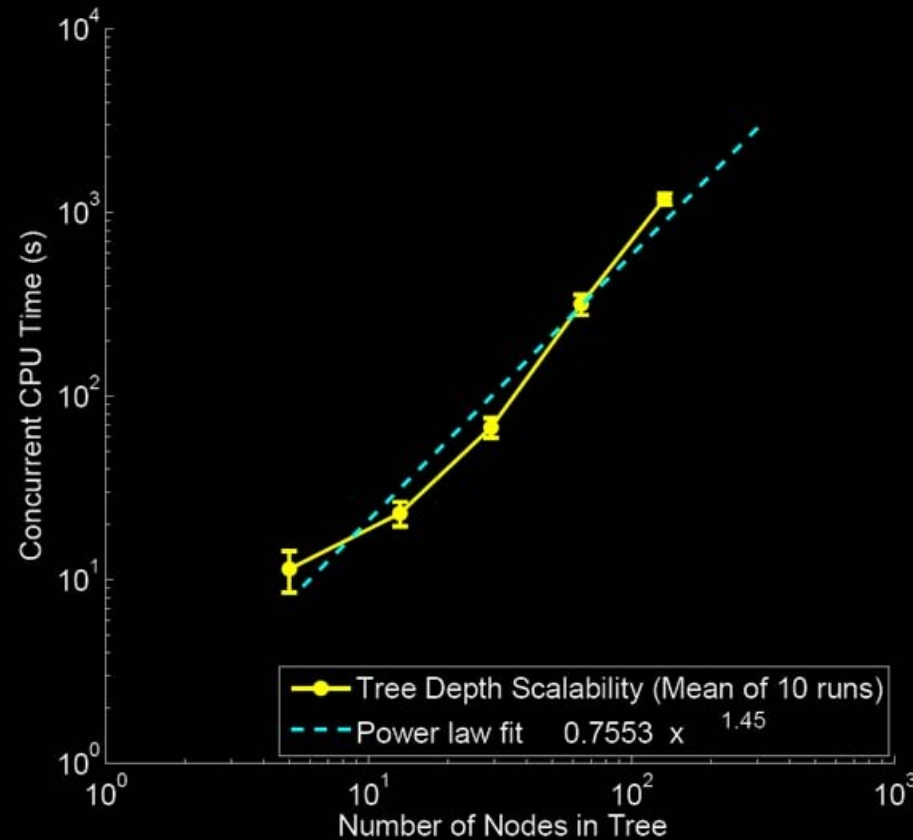
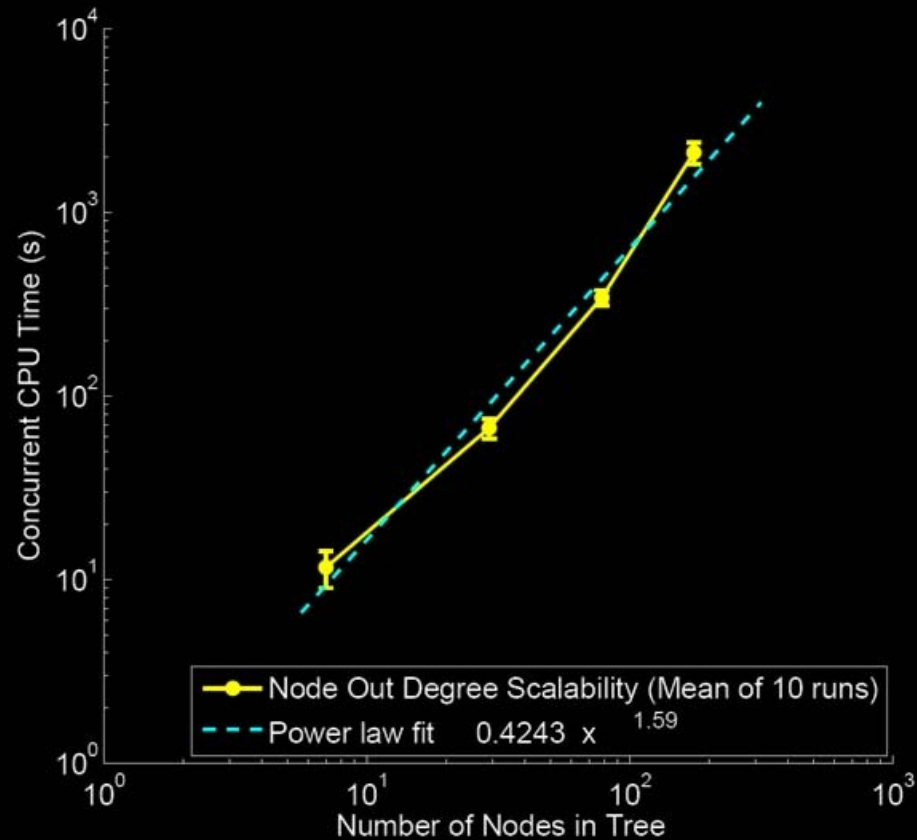


- + another activity rule in later stages

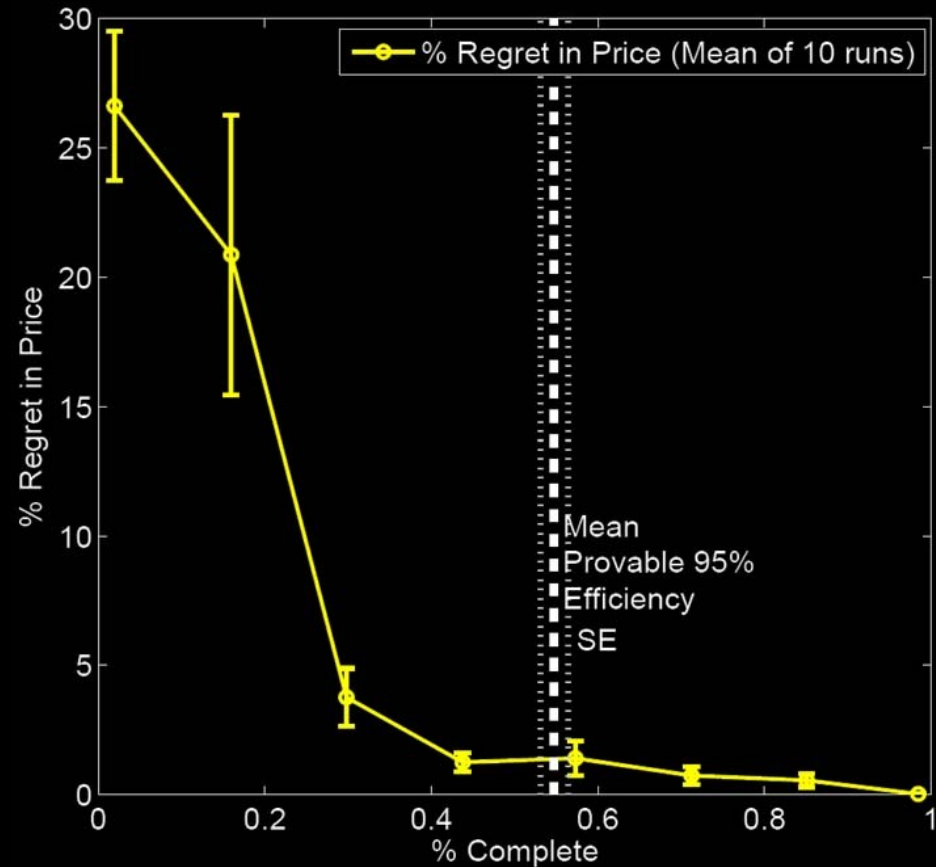
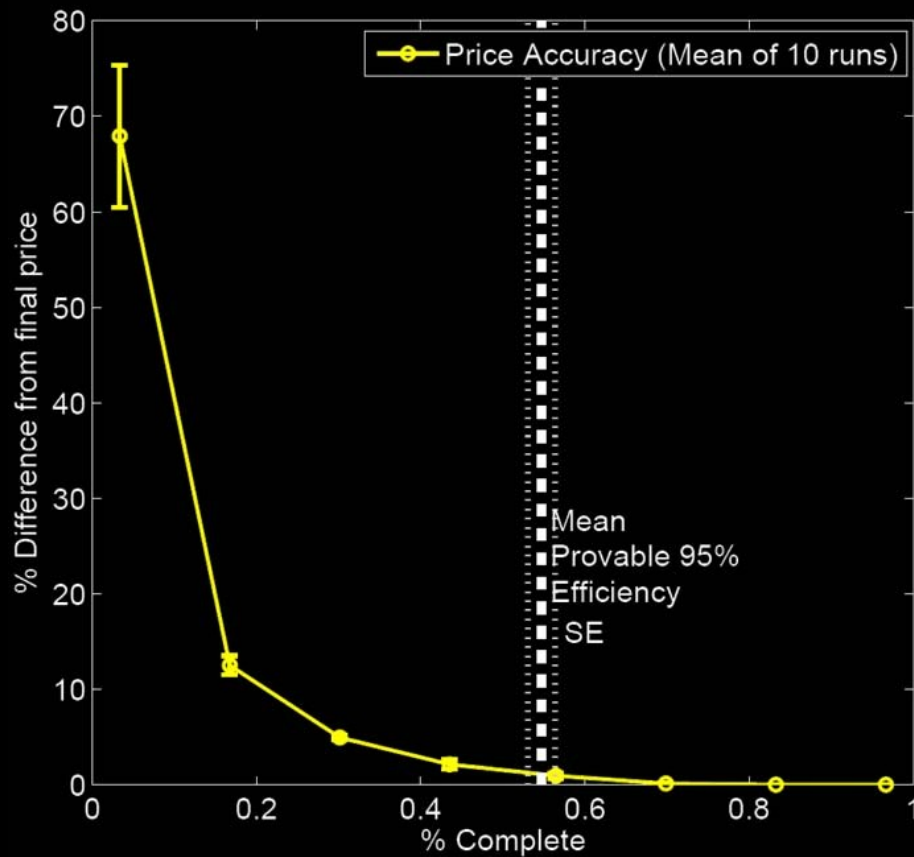
Scalability (I)



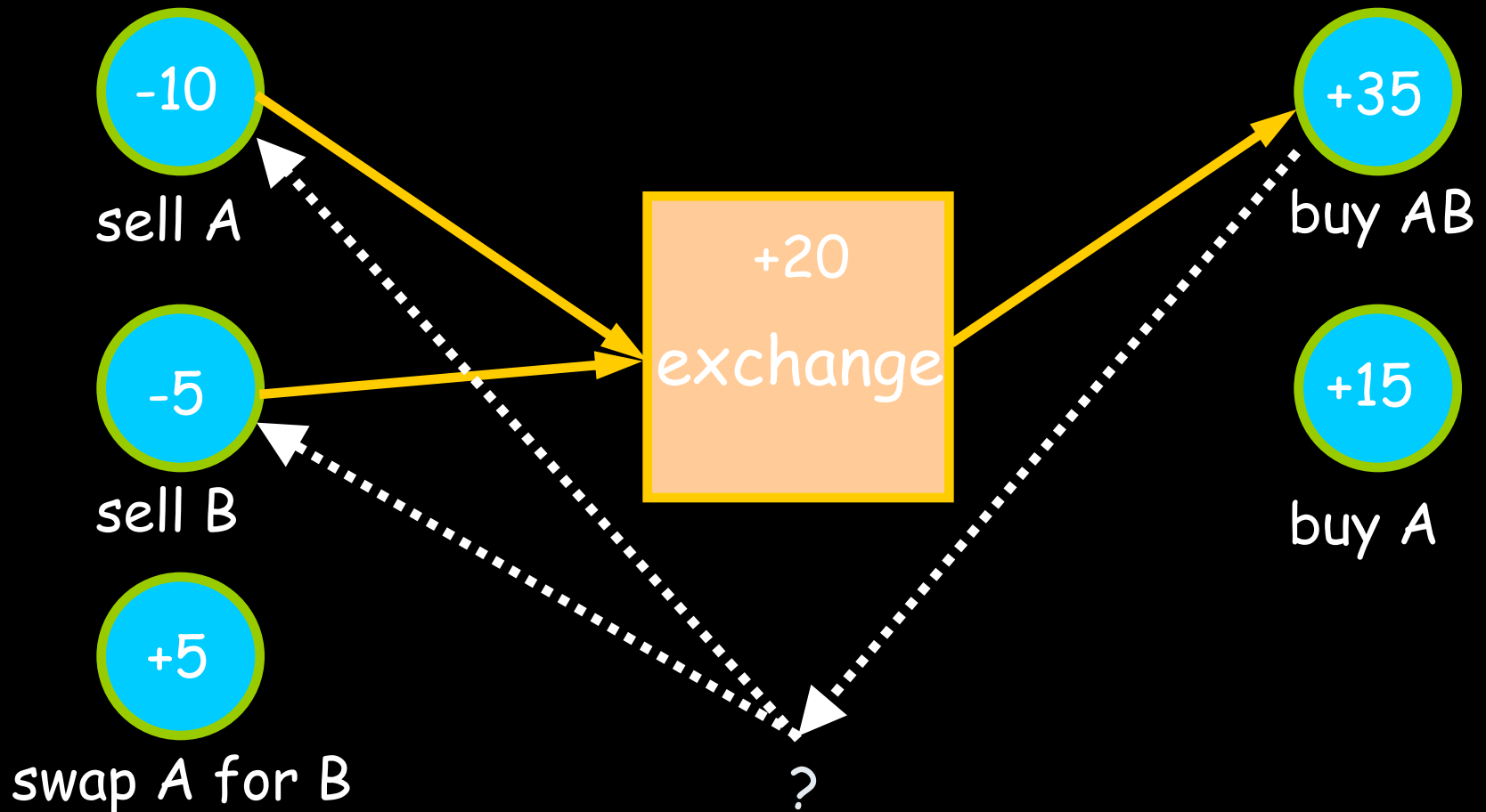
Scalability (II)



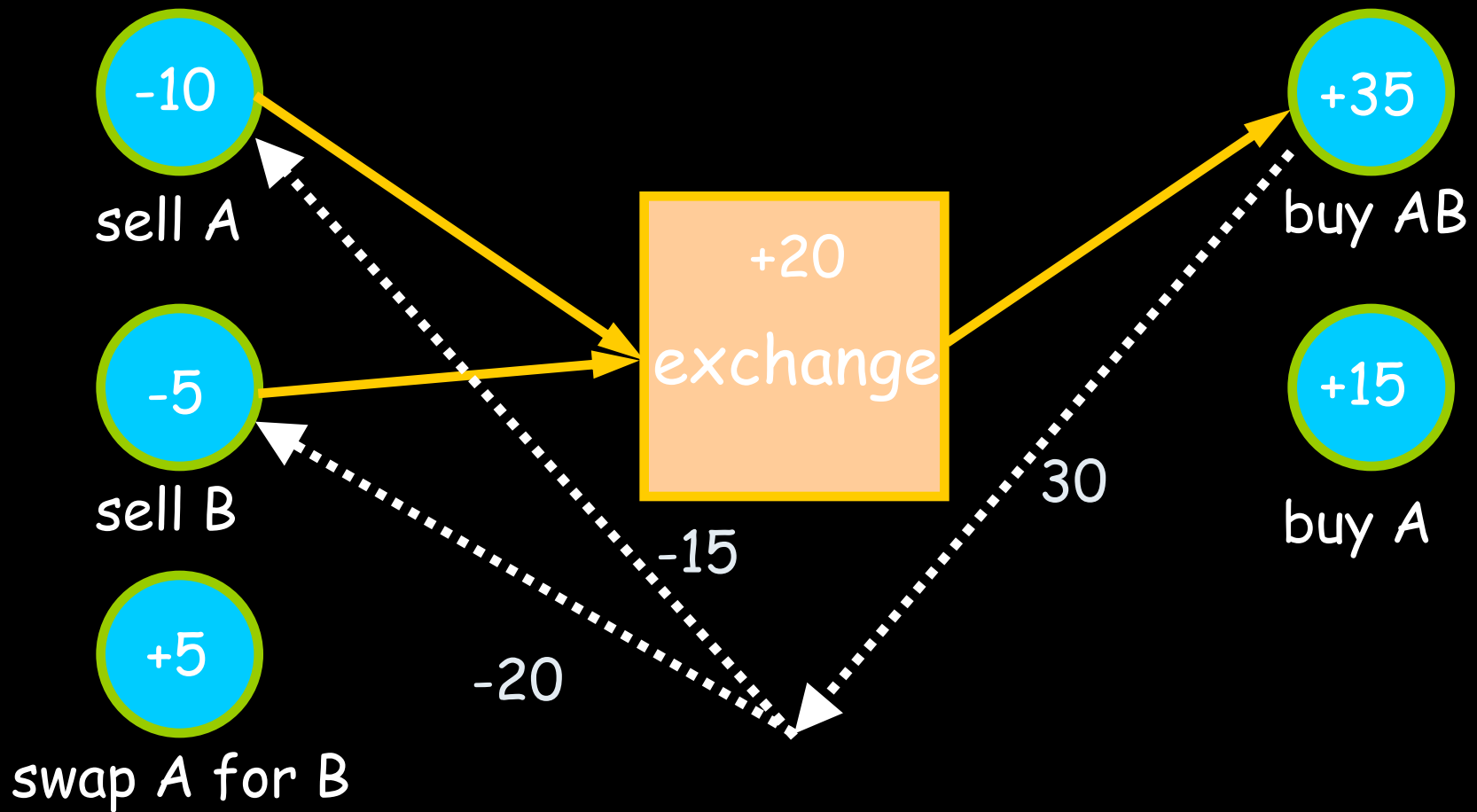
Price Feedback



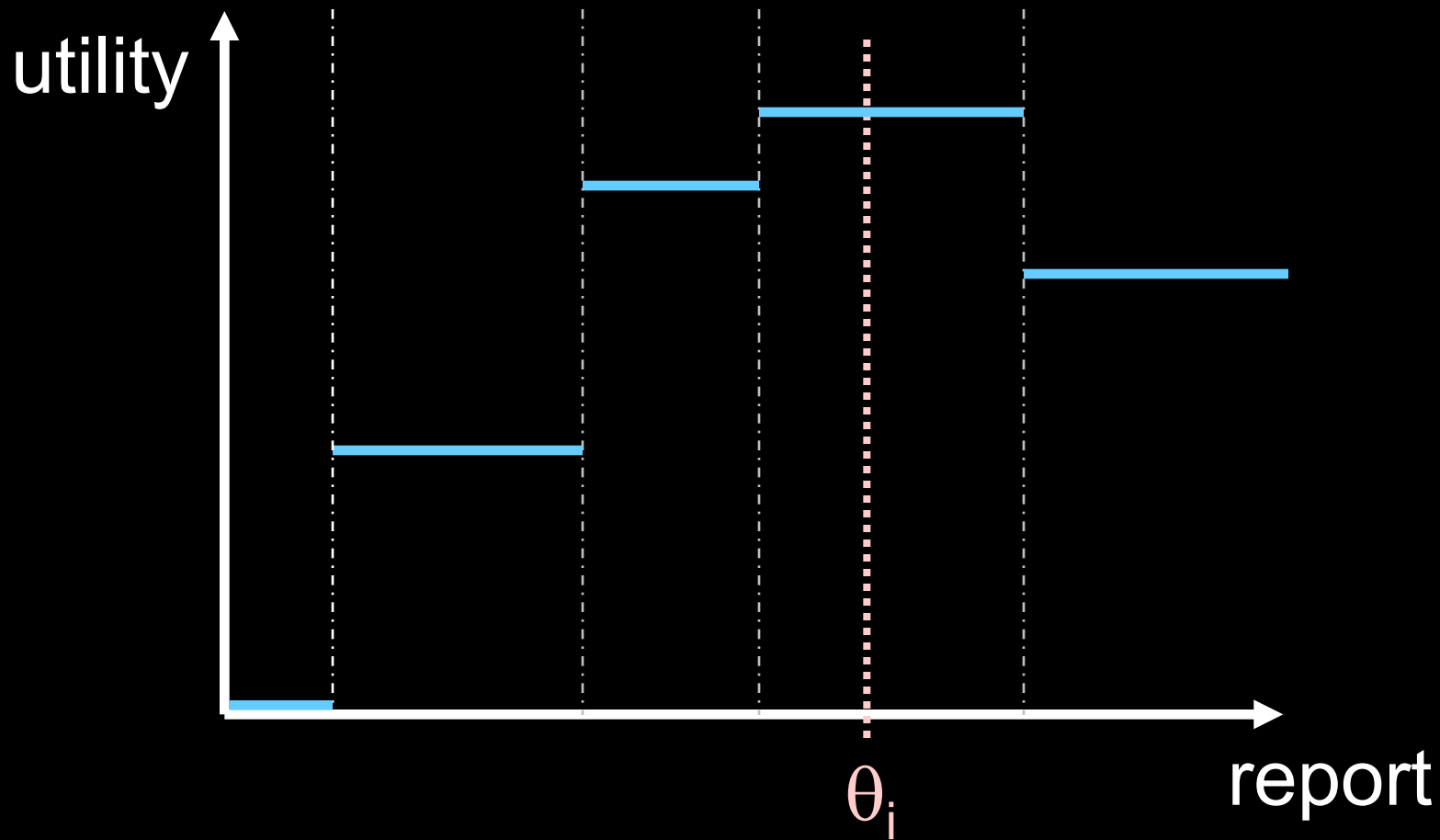
Payments?



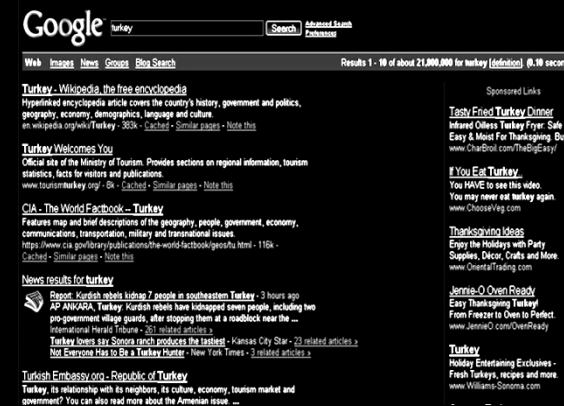
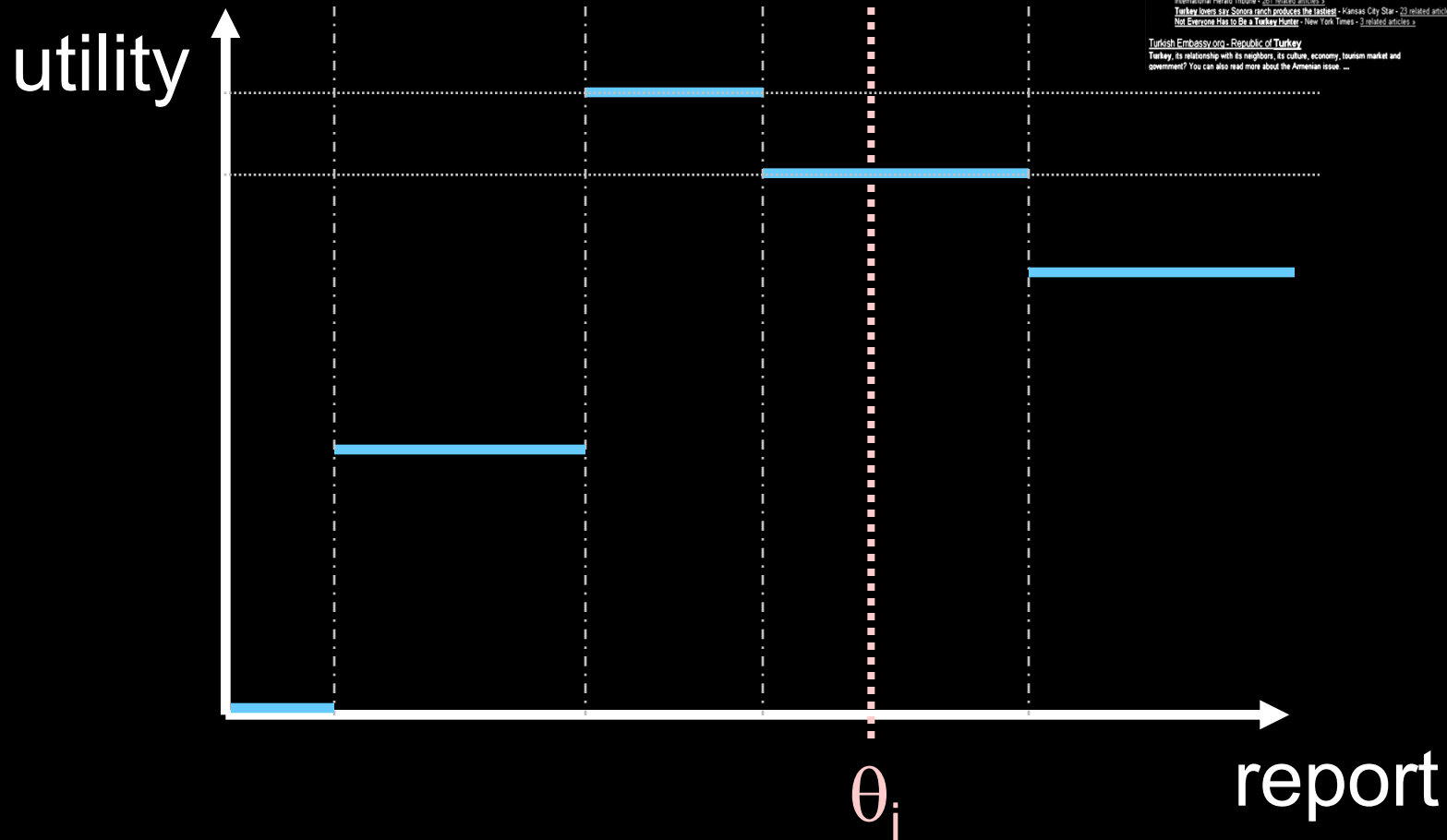
Payments: VCG?



- Myerson-Satterthwaite impossibility
 - EFF, No-deficit, IR and BNIC



Approx SP: GSP



How should we set payments
in a CE that clears
straightforwardly based on
bids?

($\equiv$ how should we make the
mechanism “maximally incentive
compatible”?)

Relaxing away from SP...

- We like SP for reasons of
 - equity (Roth'03, Pathak and Sonmez'08)
 - *simplify reasoning*
 - can predict properties of the mechanism

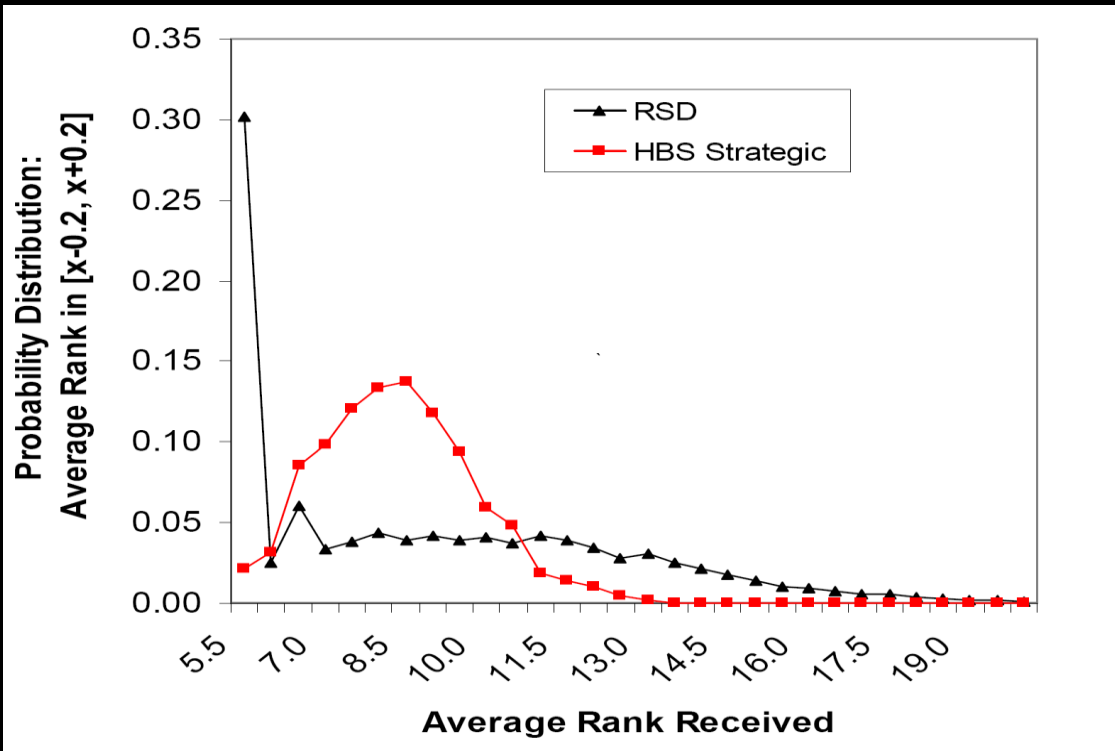
Relaxing away from SP...

- We like SP for reasons of
 - equity (Roth'03, Pathak and Sonmez'08)
 - *simplify reasoning*
 - can predict properties of the mechanism
- But it is generally hard to obtain
- And, can be provably bad along other dimensions ☹
 - e.g., CAs with complements
(Ausubel & Milgrom'06, Rastegeri, Condon, & Leyton-Brown'10)

Example: Course Allocation

(Budish and Cantillon'08)

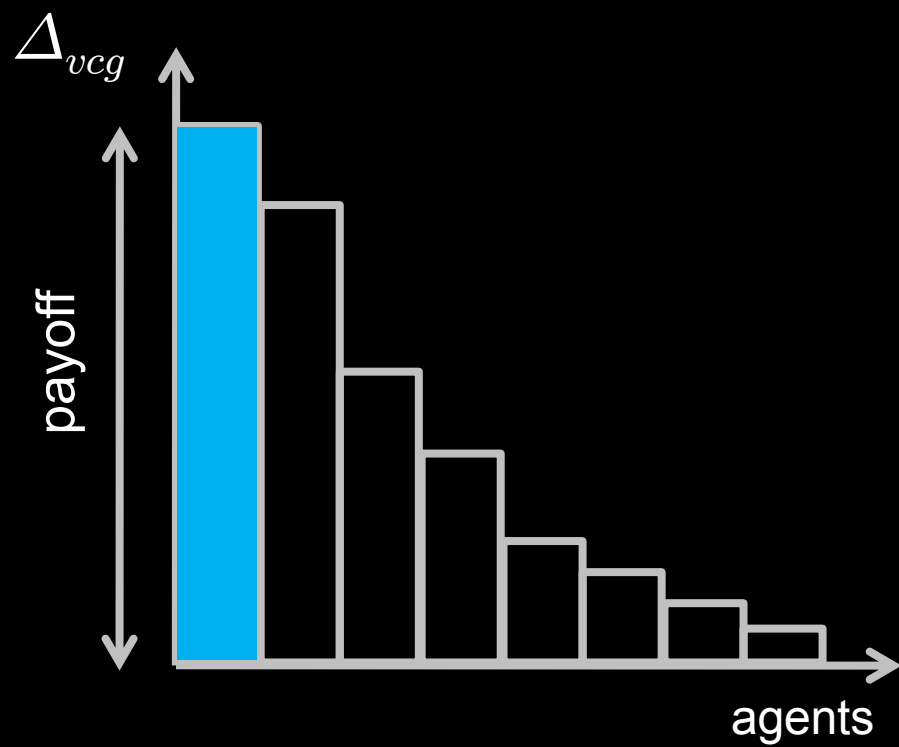
- Random Serial Dictatorship
 - basically unique amongst SP mechanisms (Papai'01)
- HBS mechanism:
 - snake back and forth, pick one at a time

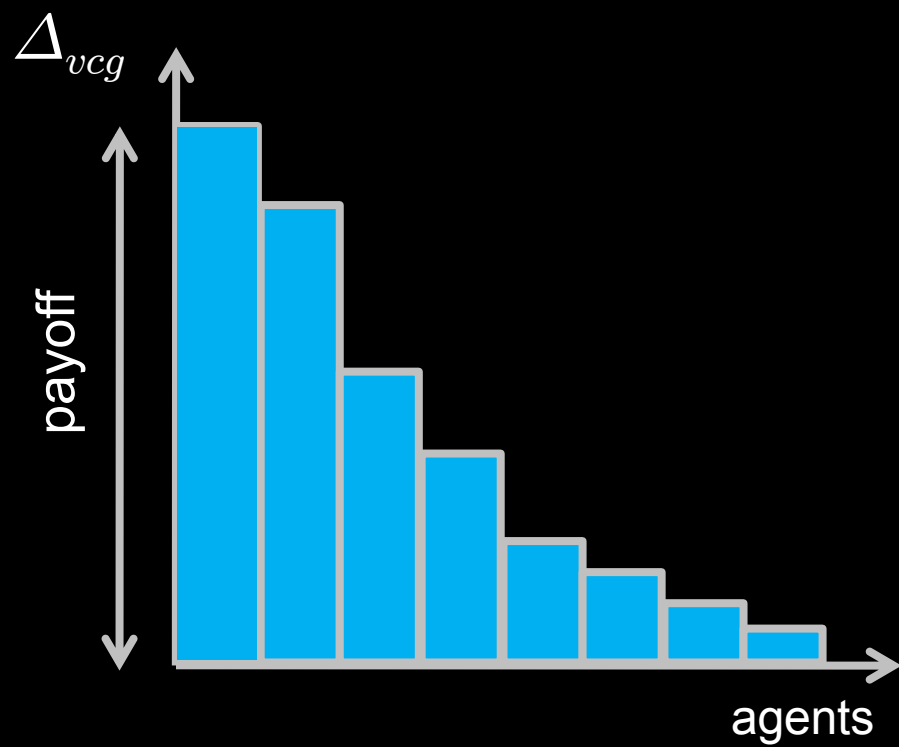


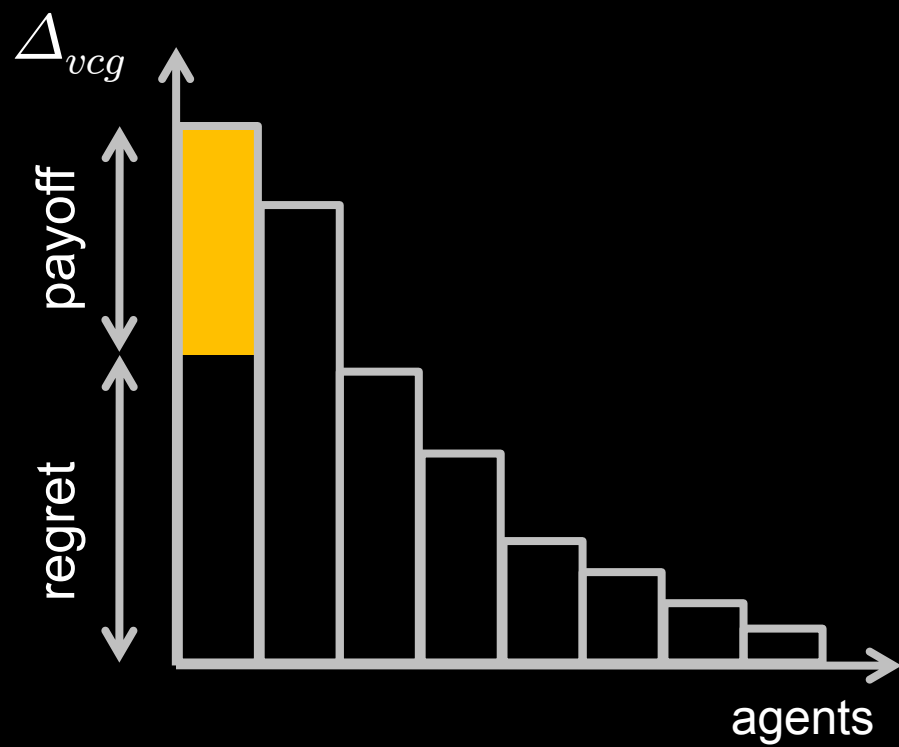
“callousness of
RSD”
(allocating 10
courses)

Old Favorite: Min Max Regret

- Regret = best utility – actual utility
- Maximally SP: minimizes max regret across agents on every instance
- ϵ -SP: $\max \text{ regret} \leq \epsilon$

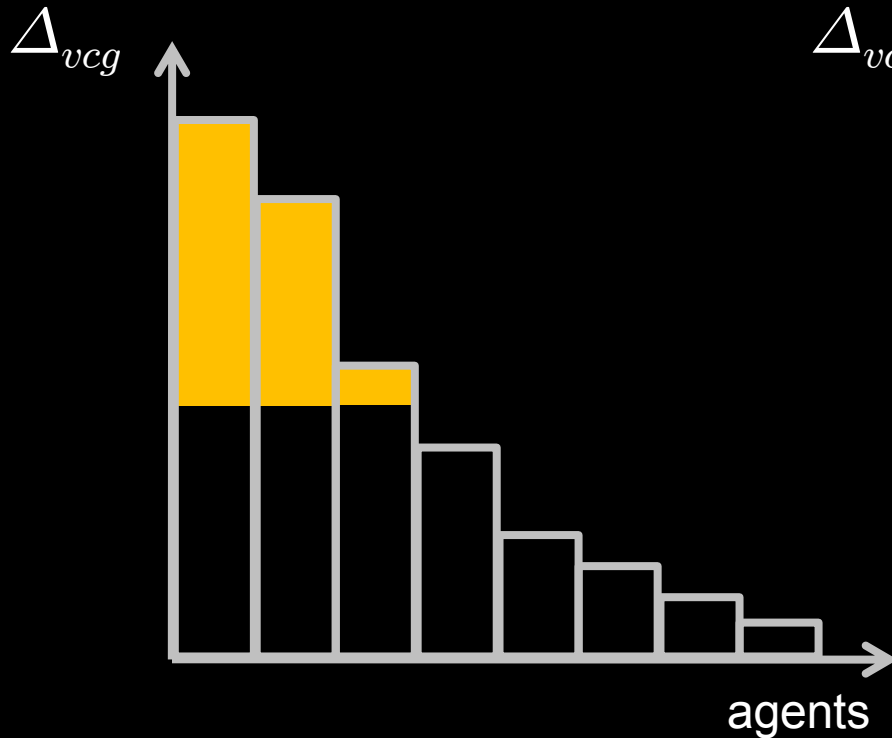




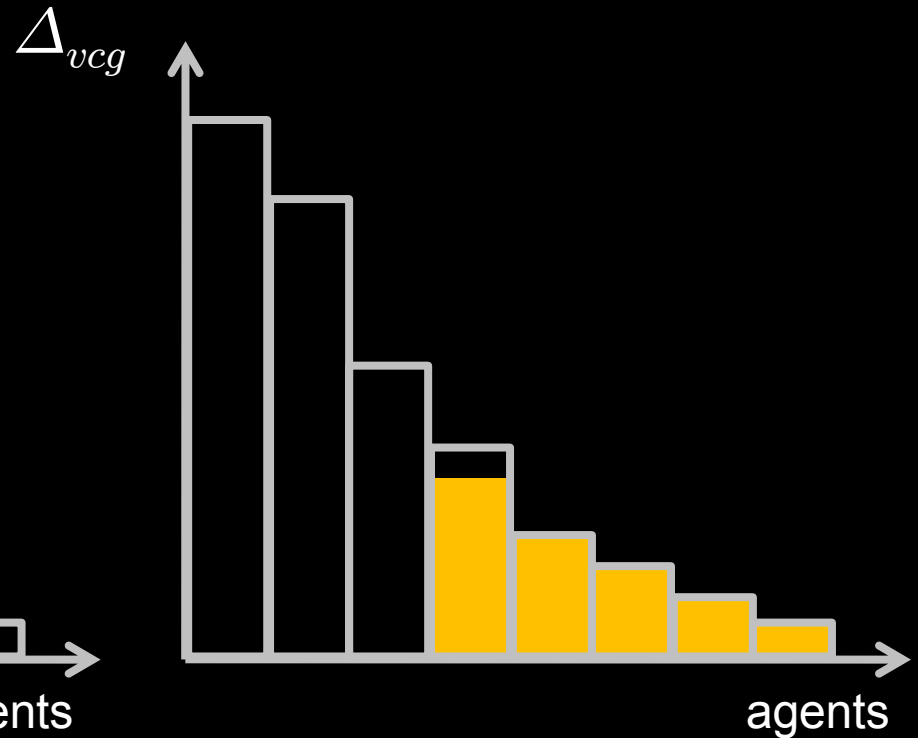


Two mechanism rules

(Parkes, Kalagnanam and Eso '01)



Threshold rule
(min max regret)



Small rule
max # (regret=0)

Back to Example

- $\Delta_{\text{vcg}} = (5, 15, 5)$ Surplus 20
 - *Threshold*: $\Delta_1 = 3.33$, $\Delta_2 = 13.33$, $\Delta_3 = 3.33$
 - payments $(-13.33, -18.33, +31.67)$
 - regret = 1.33 for all agents
 - *Small*: $\Delta_1 = 5$, $\Delta_2 = 10$, $\Delta_3 = 5$
 - payments $(-15, -15, +30)$
 - regret = 0, 5, 0
 - **Theorem.** Threshold rule minimizes ex post opportunity for gain across simple CEs
 - “truthful most often” (assume cost C_d)
- [Milgrom]

Compute approx BNE

(Related: Vorobeychik et al.)

- Single-minded CEs
- Need a way to compute approximate, restricted BNE
- Approach: assume piecewise linear, symmetric strategy profiles
- Buy: bid $(1+\alpha) v$
- Sell: bid $(1+\alpha) v$
 - Use $(\alpha_1, \alpha_2, \alpha_3)$

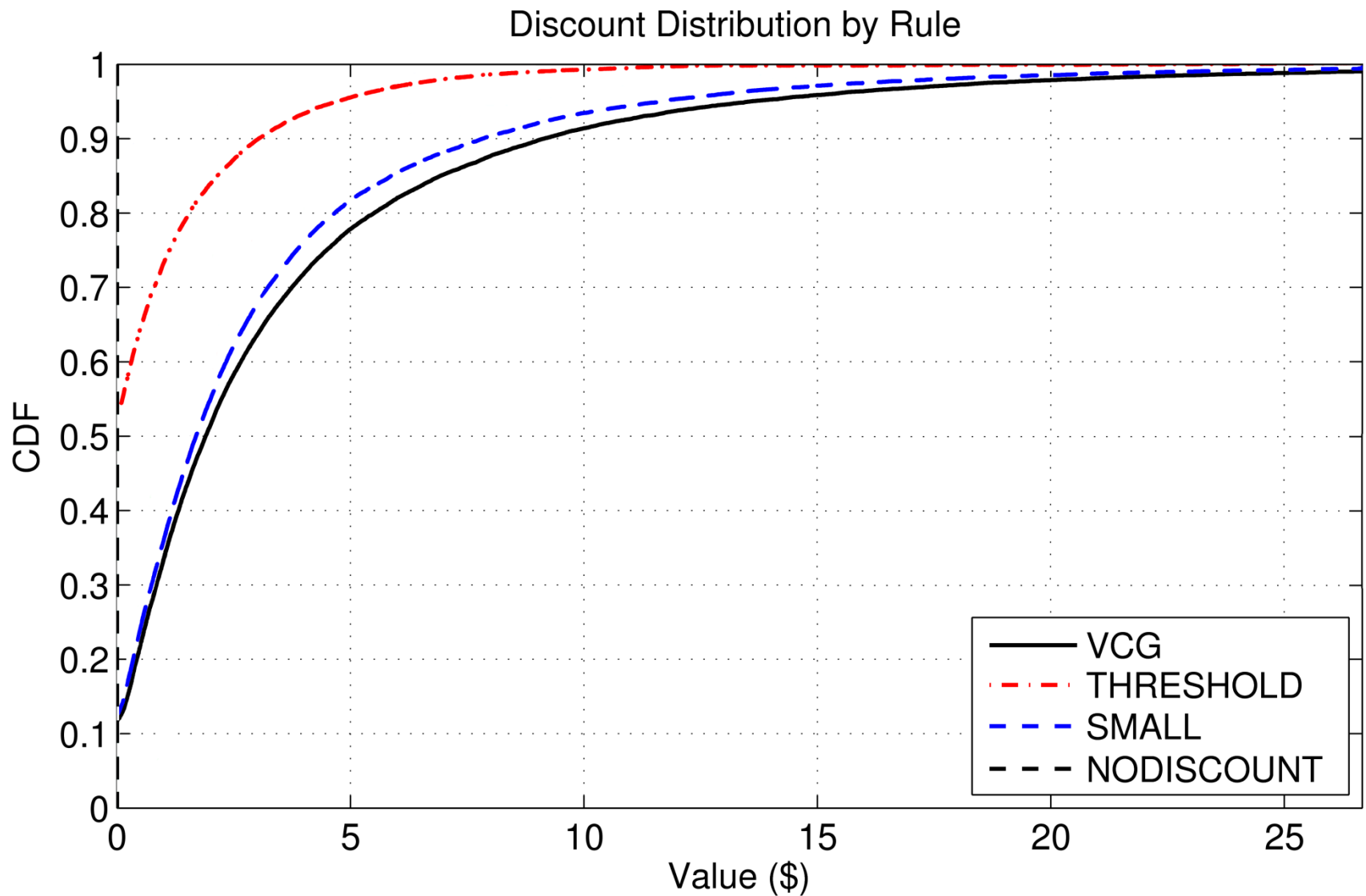
Approximate BNE Analysis

(Lubin & Parkes '09)

	strategy			efficiency		
Rule	Dec.	Uni.	Sup.	Dec.	Uni.	Sup.
<i>VCG</i>	<i>0.0</i>	<i>0.0</i>	<i>0.0</i>	<i>100</i>	<i>100</i>	<i>100</i>
Two Triangle	0.1	0.4	5.6	99.99	100	97.95
Threshold	14.6	27.2	11.2	93.64	81.09	89.74
Small	0.0	0.1	0.2	99.99	100	100
¹ No Discount	62.3	80.9	72.4	34.15	50.11	48.21

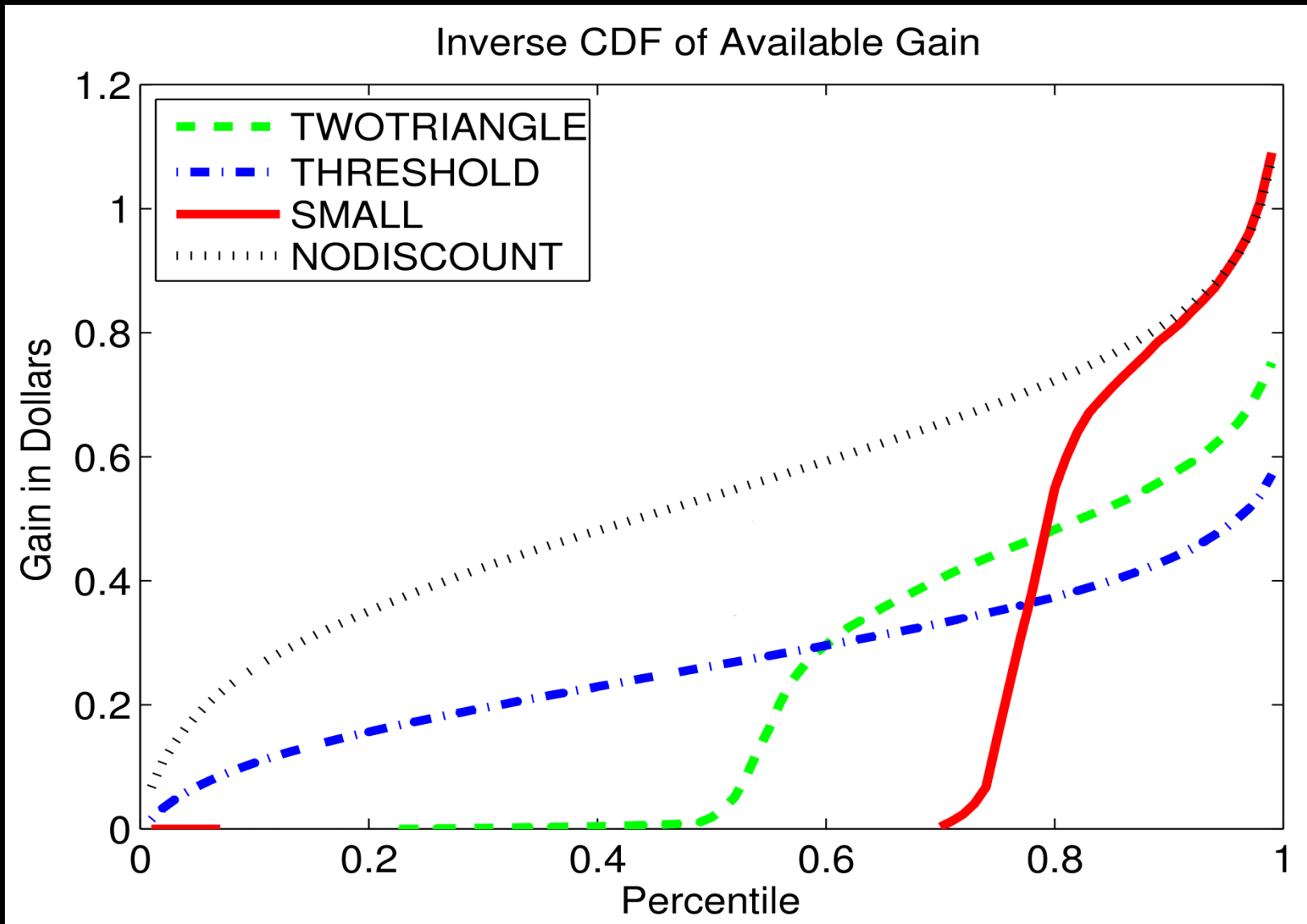
(For BNE, see Vorobeychik & Wellman'08,
Rabinovich, Gerding, Polukarov & Jennings'09)

Distributional View: Payoffs



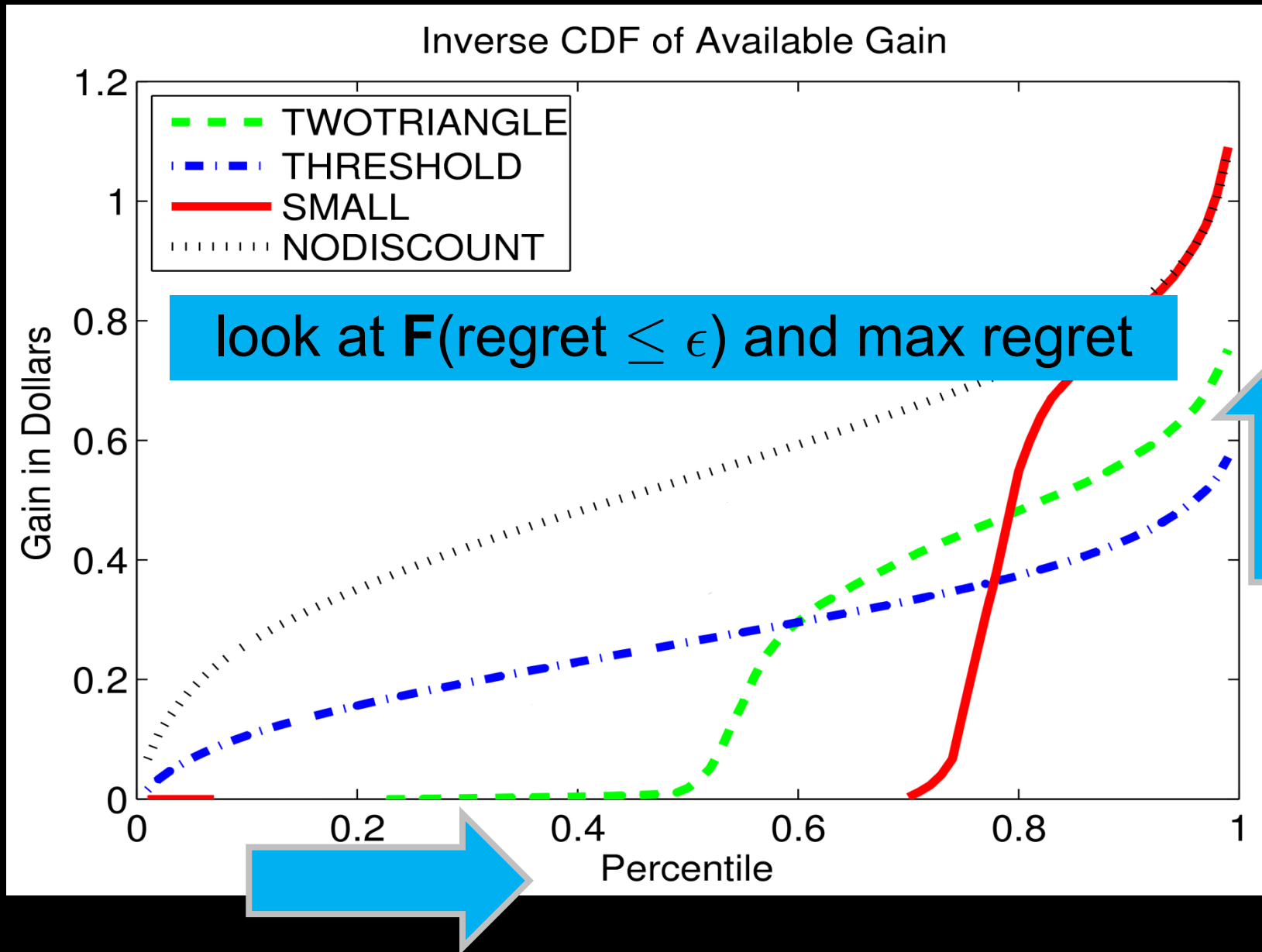
Regret Quantiles

(Lubin PhD '10)



Regret Quantiles

(Lubin PhD '10)



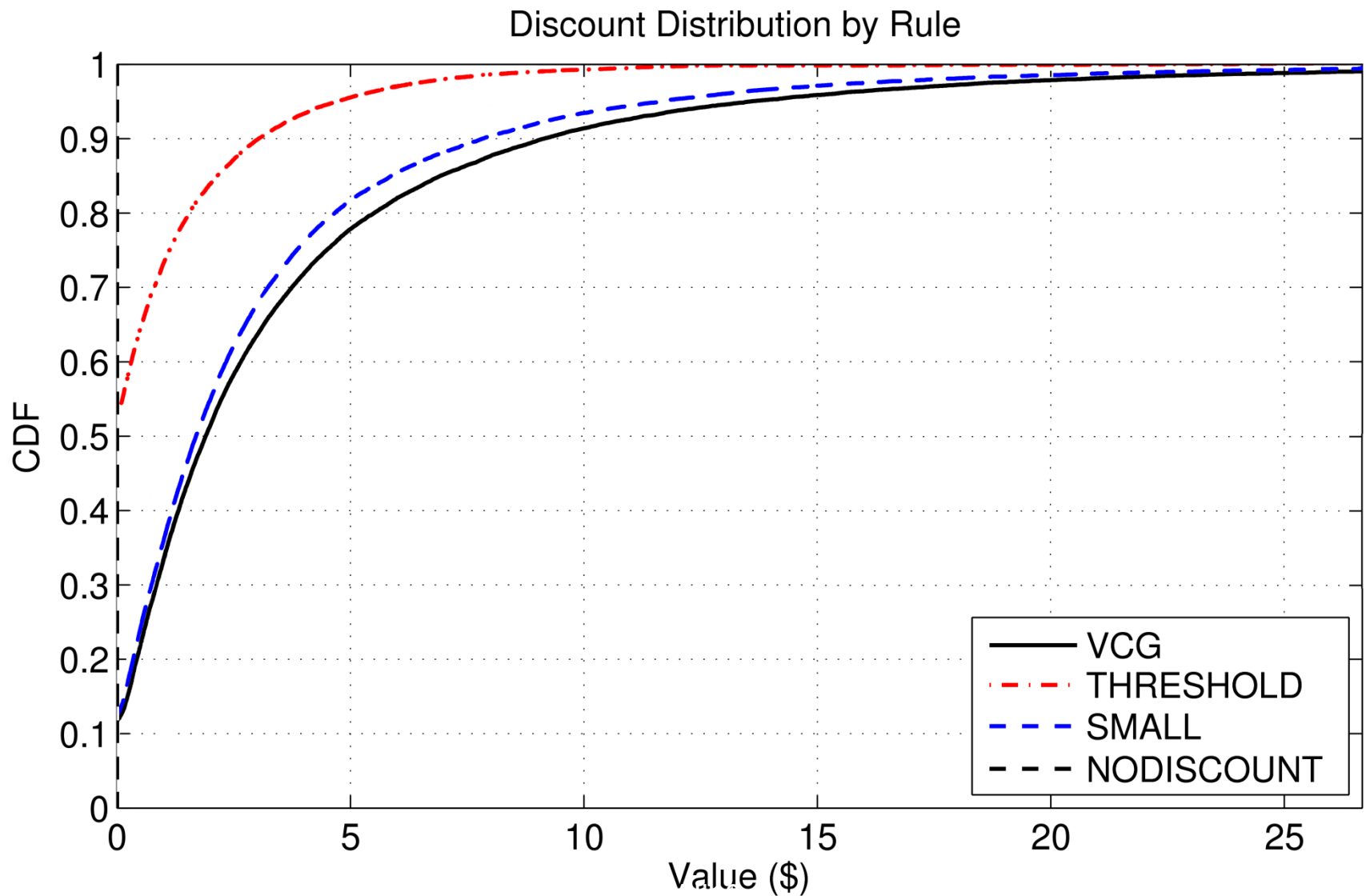
Hypothesis I

- Maximizing the number of agents with zero regret provides less *ex ante* incentive for strategic behavior than minimizing the maximum regret.
- (... proof would require reasoning about distributional properties)

Hypothesis II

- Consider a strategyproof “reference” mechanism M^* with the same allocation rule but a different payment rule
- Reducing the divergence between the distribution on payoffs in M' and the distribution on payoffs in M^* reduces the *ex ante* incentive for strategic behavior.

Distributional View: Payoffs



$$KLnorm(m) = \int_0^\infty \hat{H}^*(\pi) \log \left(\frac{\hat{H}^*(\pi)}{\hat{H}^m(\pi)} \right) d\pi$$

$$L_1(m) = \int_v ||\pi_+^*(v), \pi_+^m(v)||_1 g(v) dv \quad (2)$$

$$L_1 norm(m) = \int_v ||\frac{\pi_+^*(v)}{V^*(v)}, \frac{\pi_+^m(v)}{V^*(v)}||_1 g(v) dv \quad (3)$$

$$L_2(m) = \int_v ||\pi_+^*(v), \pi_+^m(v)||_2 g(v) dv \quad (4)$$

Discriminative power of metrics

Correlation with Efficiency at Truth			
Metric	Corr.	ρ -value	Significant?
$KLnorm$	-0.3814	0.0044	Y
$L_1 norm$	-0.1698	0.2197	N
$L_2 norm$	0.0154	0.9120	N
$L_\infty norm$	0.0220	0.8745	N

Correlation with Mean Shave at Truth			
Metric	Corr.	ρ -value	Significant?
$KLnorm$	0.3794	0.0047	Y
$L_1 norm$	0.1610	0.2447	N
$L_2 norm$	-0.1001	0.4712	N
$L_\infty norm$	-0.1147	0.4087	N

Table 3: Correlation between metrics evaluated at truth and both efficiency and the amount of shaving, considering all 54 conditions (Significance at 0.05 level)

Other Approx SP Concepts

- SPITL: SP in a large market (Budish'09)
 - get best outcome in choice set
 - choice set becomes agent-independent in limit of continuum market
- Counting manipulations (Pathak & Sonmez'09)
 - (roughly) B manipulable by less agents in less instances than A
- Marginal gain (Erdil & Klemperer'09)
 - minimize $|\partial \pi_i(v_i, b_{-i}) / \partial v_i|$

Conclusion

- Incentive-efficient CEs are only known for simple settings (e.g., known single-minded bidders; one buyer, one seller, single unit)
- ICE = bidding language, winner determination, price feedback, proxy agents
- Payment design
 - “small” $\gg$ “threshold”
 - maximize # agents with zero regret
 - or, minimize divergence to VCG payoffs