

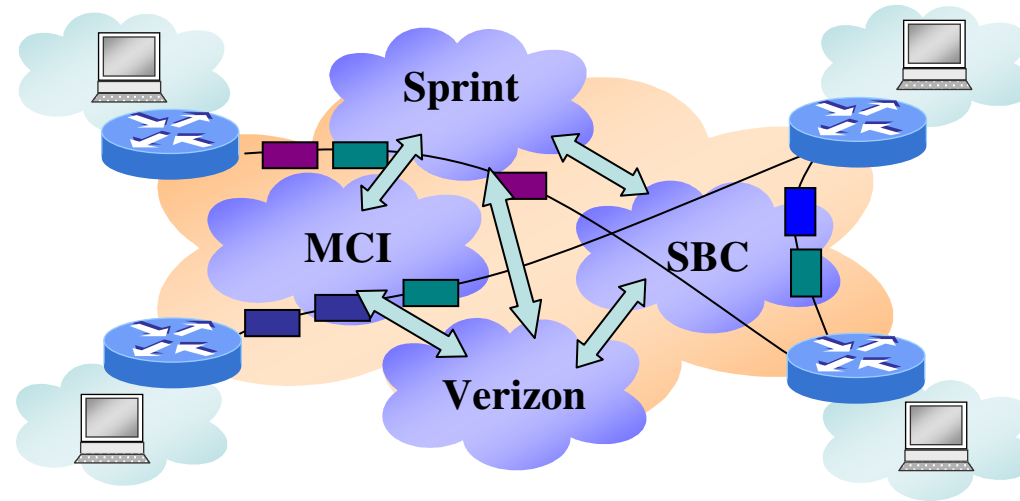
An Experimental Analysis of a Combinatorial Market Mechanism for Bandwidth Trading

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Outline

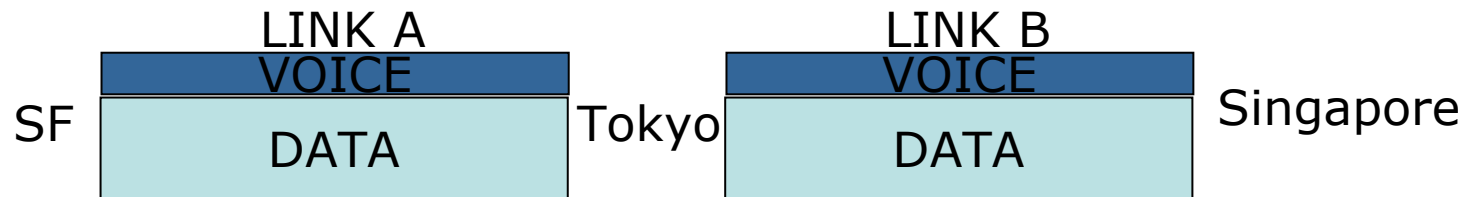
- Introduction to bandwidth markets
- Combinatorial exchanges
- Theoretical setup
- Experimental Approach
- Simulation Approach
- Conclude

Introduction



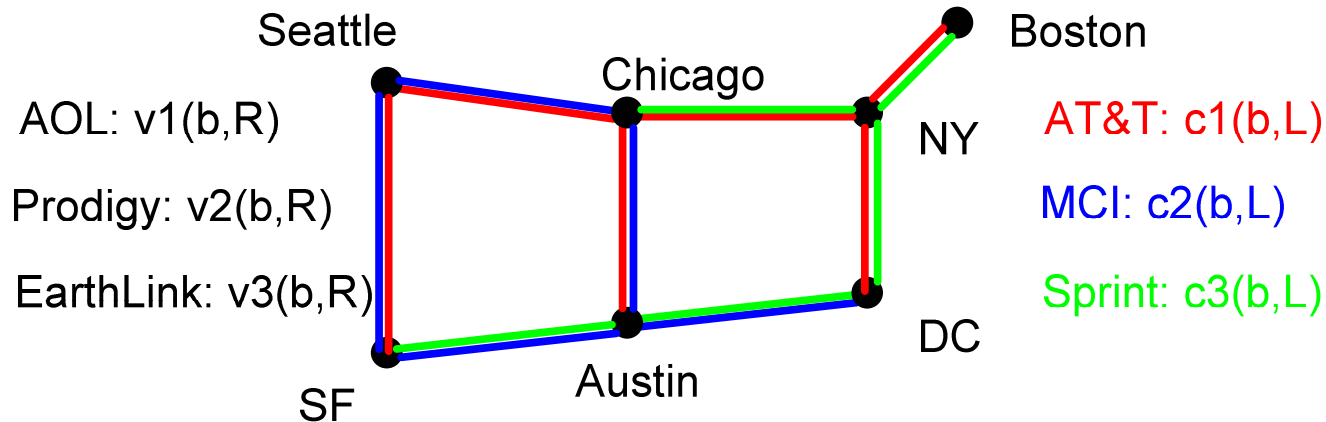
- Need Auction/Exchange Mechanisms that achieve market efficiencies
 - Maximize each agent's surplus
 - Maximize Auctioneer/Exchange revenue
 - Need Liquidity

Bandwidth Exchanges



- *Bandwidth Exchanges: Arbinet, Band-X.com, InvisibleHand networks, Enron!, RateXchange!*
 - Buyers and Sellers. Voice and Data (QoS). Spot and (potentially) Futures Markets.
 - Technology for switching peering arrangements in real-time (MPLS, Traffic Eng.)
 - Non-combinatorial economic mechanism

A Combinatorial Bandwidth Exchange

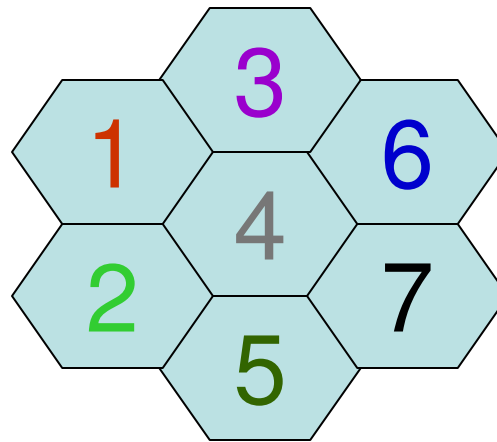


- Service-providers need routes, i.e. bandwidth over links, hence *bundles*
 - Bandwidth is an *indivisible* commodity
- Need a *market mechanism* which maximizes social welfare (utility delivered – cost incurred)

FCC Spectrum Auctions

T-mobile {1,3,4}

Cingular {3,4,6}



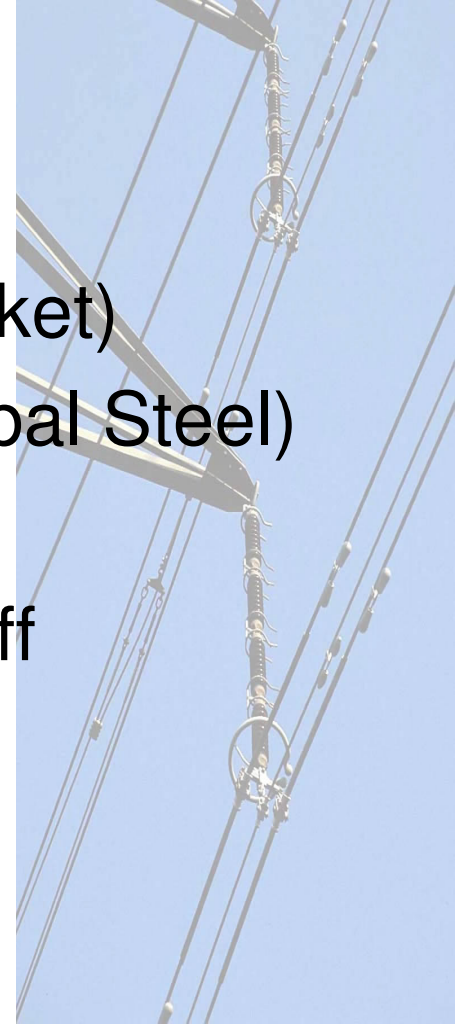
Sprint {2,4,5}

Verizon {4,5,7}

- Wireless-providers want bundles of cells
 - Spectrum is an *indivisible* commodity
- Poor auction design can lead to inefficient market allocations

Other Applications!

- Best suited for markets with complementarities
 - Electricity Markets (\$50 Billion market)
 - Procurement Auctions (Sears, Global Steel)
 - Financial Markets (NASDAQ)
 - Scheduling: Air-Crew, Hospital Staff
 - Grid Computing, e.g., PlanetLab
 - Wi-Max (Spectrum Auctions ?)



Mechanism Design Issues

- Auctions
 - Market Mechanism
 - Single vs. Double Sided
 - Information Revelation
 - Open cry vs. Sealed-bid vs. Iterative (combinatorial cases)
 - Pricing
 - Uniform vs. Discriminatory
 - Bidding:
 - Single unit bidding
 - Bundle bidding
 - Logical Constraints (XOR, OR)
- Desirable properties
 - Efficiency, Incentive-compatibility, Revenue Maximization

Combinatorial Sellers' Bid Double Auction Mechanism (Jain & Varaiya, 2004)

- Buyer i demands up to δ_i bw on bundle R_i and bids $\$b_i$ (v_i)/unit
- Seller j offers up to σ_j bw on L_j and asks $\$a_j(c_j)$ /unit
 - **Mechanism:** Maximize *social welfare* subject to *demand \leq supply* constraint:

$$(x^*, y^*) \in \arg \max \sum_i b_i x_i - \sum_j a_j y_j$$

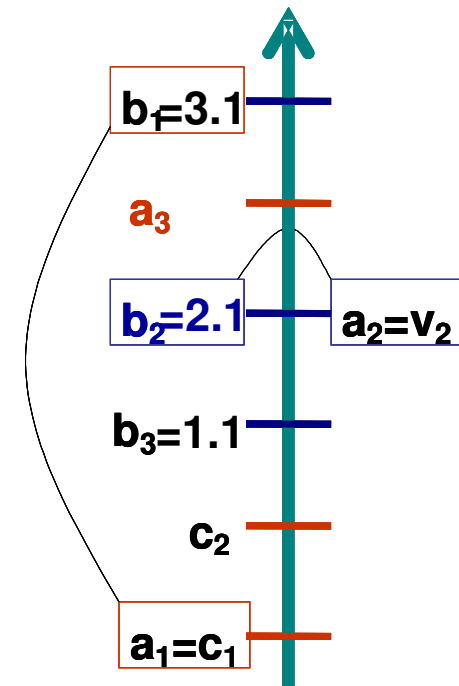
$$\text{s.t.} \quad \sum_{j:l=L_j} y_j - \sum_{i:l \in R_i} x_i \geq 0, \forall l,$$

$$x_i \in \{0, 1, \dots, \delta_i\}, \quad y_j \in \{0, 1, \dots, \sigma_j\}.$$

- Prices on items by $p_l^* = \sup \{ a_j : y_j^* > 0, l = L_j \}$
(highest ask price of a matched seller on an item)

Example of SeBiDA

- Single link Network.
 - Three Buyers with valuations \$1.1, 2.1, 3.1 resp.
 - Three Sellers with costs \$1, 2, 3 resp.
 - Social Welfare = $y_1(3.1 - 1) + y_2(2.1 - 2) + y_3(1.1 - 3)$
 - First two buyers and first two sellers matched. Price on link = \$2.



Theoretical Results

- Complete information: efficient and budget-balanced, almost always incentive compatible
 - Bidding truthfully is the dominant strategy for all except the matched seller with the highest bid on each item
- Incomplete information: asymptotically efficient, budget-balanced and Bayesian Nash incentive compatible

Experimental Validation

- Experimental economics approach
 - Induced value theorem
 - Provide valuations thus controlling market structure
 - Observe bidding behavior under different market conditions
- Testing the efficiency of the mechanism and behavioral strategies
- Adapt design towards better efficiency and better understanding of strategy space

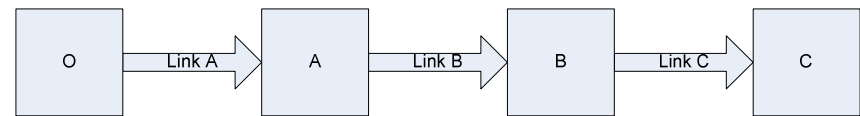
Experiment Setup

Trunks	A	B	C	AB	BC	AC	ABC
1	17	15	11	37	30	28	48
2	33	29	21	72	58	54	93
3	49	43	31	107	86	80	138

Buyer Valuations

Trunks	A	B	C
1	6	5	8
2	12	10	16
3	18	15	24

Seller Valuations



Simple Network

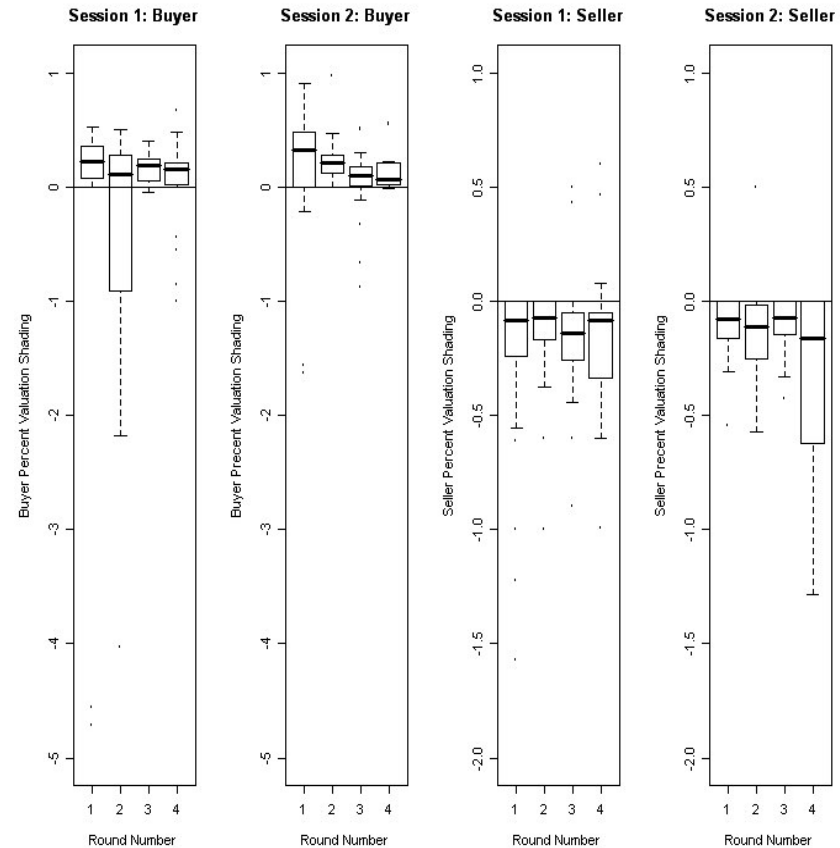
Experimental Results: Efficiency

- average efficiency of the mechanism
 - 67% in the session 1
 - 87% in the session 2
- Error in bidding in session 1 round 2 let to efficiency loss
 - Removing error leads to 78% efficiency

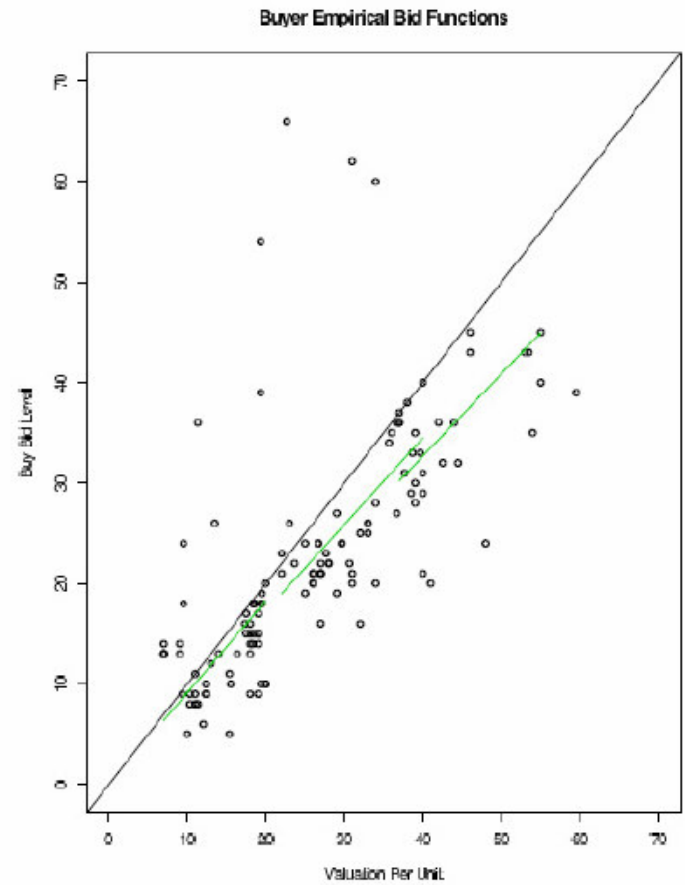
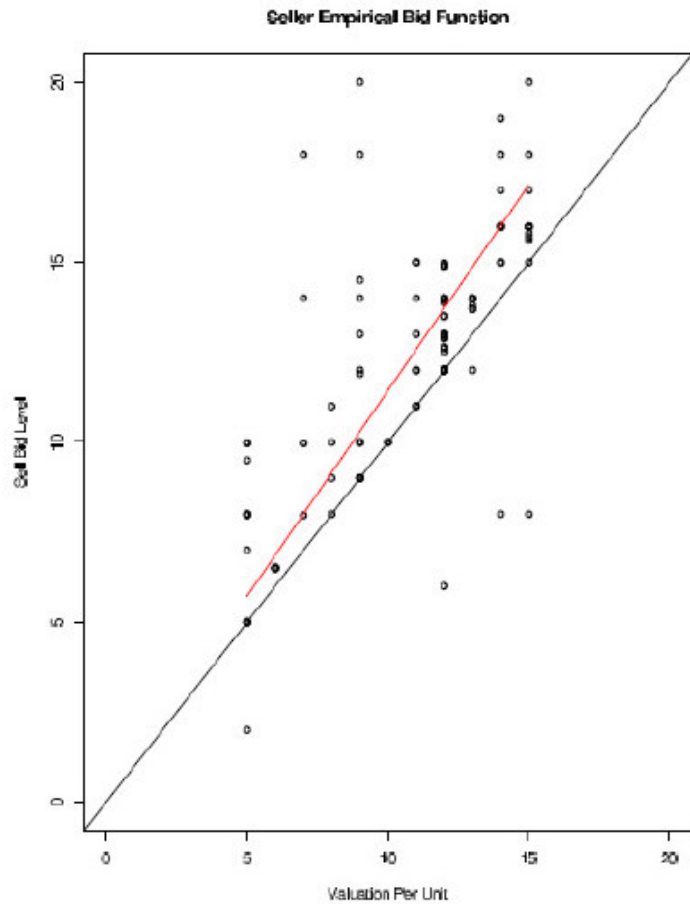
Round	Session 1	Session 2
1	66.67	83.02
2	41.03	92.71
3	91.11	83.74
4	77.67	88.59

Results: Shading Behavior

- Buyers get closer to truthful revelation as they learn the game
- There is not trend in sellers' behavior



Empirical Bidding Functions



First Model: Single-shot Sebida

- Use empirical bidding functions adding an error term
- Uniform random draw between buy strategies
- Different numbers of participants
- 30 scenarios per buyer-seller combination
- Average efficiency at 88%

AVERAGE EFFICIENCY VALUES FOR THE FIRST MODEL

Buyers	Sellers	Avg. Efficiency (%)	Std.Dev
10	15	89.41	7.37
20	30	88.62	5.33
30	45	88.62	4.35
40	60	87.67	3.31
50	75	87.52	3.25
60	90	89.01	2.62
70	105	88.65	2.29
80	120	89.20	2.23
90	135	88.51	1.83
100	150	88.04	2.31

Second Model: Iterative Sebida

AVERAGE EFFICIENCY VALUES FOR THE SECOND MODEL

- Iterative version of the Sebida auction format
- Risk averse bidders – single bid per participant
- 30 market conditions per buyer-seller combination
- Adjustment Propensity
 - Buyers (Sellers) increase (decrease) bid price incrementally if not successful
 - Buyers (Sellers) decrease (increase) bid price incrementally if successful
- Terminate after trivial welfare increase per round
- Average efficiency above 90%

Buyers	Sellers	Avg. Efficiency (%)	Avg. Rounds
10	15	79.37	16
20	30	87.09	23
30	45	91.83	23
40	60	91.81	25
50	75	92.82	30
60	90	92.88	29
70	105	93.48	24
80	120	94.12	30
90	135	94.55	42
100	150	93.23	30
1000	1500	96.81	59

Conclusions

- Perverse bidding strategies lead to decreased efficiency (67% vs. 88%)
- Static: Increasing number of market participants maintains similar levels of efficiency but reduces variability
- Iterative: Increasing number of rounds increases efficiency and reduces variability