Topic 19 – Auctions

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Course in Behavioral and Experimental Economics

A tribute to Vernon Smith

Teaching auction experiments in a course on experimental economics must reach the point where Vernon Smith is mentioned as a pioneer in auction experiments.

In 2002, he received the Nobel Prize in Economics for “having established laboratory experiments as a tool in empirical economic analysis, especially in the study of alternative market mechanisms“.

In particular, Vernon Smith recognized world-wide fame for his early experimental contributions (in the 1960ies) on the double-auction and the prerequisites for its convergence to the competitive equilibrium.

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What is *not* covered in this topic

The pioneering work of Vernon Smith has laid the ground for much of the experimental methodology used today as well as for most experimental research in auctions (even though that is nowadays no longer always acknowledged in the list of references).

The huge literature initiated by Smith himself and many followers could fill an own course (see the background material on the Nobel-homepage or the auction-chapter in the Handbook of Experimental Economics, 1995).

However, despite setting milestones, we will not cover the work by Smith, but concentrate on recent applications of experimental work to particular types of auctions.

What *is* covered in this topic

1) Auctions on the Internet have caught much interest in the economics community, because they yield enormous revenues and because they pose interesting challenges to market designers. We will focus on

   A) Rules for ending Internet auctions, starting with a field study by Roth and Ockenfels (2002) and corroborating the field evidence by a controlled laboratory experiment by Ariely et al. (2005).

   B) Mechanisms to increase efficiency in Internet auctions, specifically feedback systems that foster trust (Bolton et al., 2004).

What *is* covered in this topic

2) Auctions of mobile phone licences (UMTS- or third-generation spectrum auctions) have become one prominent example for the power of experimental methods (in advising the British and other governments how to set up these auctions in order to generate a large revenue). We will focus on
   A) Some design alternatives for these auctions (Abbink et al., 2005).
   B) The possible impact of teams bidding in such auctions (Sutter et al., 2007).

Internet auctions and the timing of bids

Roth and Ockenfels (2002) analyze the timing of bids in Internet auctions on eBay and Amazon.

Their study might be considered a field experiment as it tests economic behavior in a natural setting (in the field) under different circumstances.

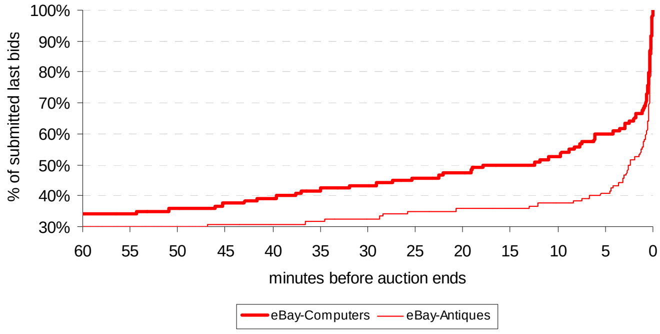
The variation is the rules for ending Internet auctions on eBay and Amazon.

The resulting timing of bids is perfectly observable and poses some puzzles.

A controlled laboratory experiment (of Ariely et al., 2005) on the influence of ending rules on the timing of bids will be presented after the field evidence.

The timing of bids – First evidence

Cumulative probability distributions of the timing of the last bid in an auction on eBay (for categories Computers and Antiques)



Share of bids

Last hour	68%
10 min	55%
5 min	50%
1 min	37%
10 sec	12%

In more than one third of auctions (in 1999/2000) the last bid in the auction enters 1 minute or less prior to the end (when auctions typically run a week!).

Why would someone want to bid late?

- eBay: "… if you had bid your maximum amount up front … the outcome would not be based on time."
- A seller: "Almost without fail after an auction has closed we receive emails from bidders who claim they were attempting to place a bid and were unable to get into eBay. … All we can do in this regard is to urge you to place your bids early."
- esnipe.com's Sicht: "… there are too many factors beyond our control to guarantee that bids always get placed. … network traffic and eBay response time can sometimes prevent a bid from being completed successfully. This is the nature of sniping."
- Roth and Ockenfels (2002) report that more than 80% of snipers had experienced the loss of a bid.

The informal game theory of sniping

- Sniping is a rational strategy against naive incremental bidding (of naive bidders with little or no experience).
- Sniping protects private information.
- Sniping protects against shill-bidding.
- Sniping makes collusion of experienced bidders more likely (thereby keeping prices low).

Timing and Amazon‘s soft ending

“We know that bidding may get hot and heavy near the end of many auctions. Our Going, Going, Gone feature ensures that you always have an opportunity to challenge last-second bids. Here's how it works:

whenever a bid is cast in the last 10 minutes of an auction, the auction is automatically extended for an additional 10 minutes from the time of the latest bid.

This ensures that an auction can't close until 10 ‘bidless’ minutes have passed.“

[Amazon.com]

Amazon's soft ending and sniping

Amazon's soft ending-rule eliminates the benefits of sniping, because

- A sniper whose bid gets lost in the last seconds (of the original end time) can always submit another bid if just one other bidder/sniper was successful with a bid in the last 10 minutes.
- An uninformed/inexperienced bidder can always see the bids of the more experienced bidders (for at least 10 minutes).
- A naive (incremental) bidder or a shill-bidder can always react to a bid that was placed close to the original end-time.

→ Sniping is no longer a best-reply on Amazon.

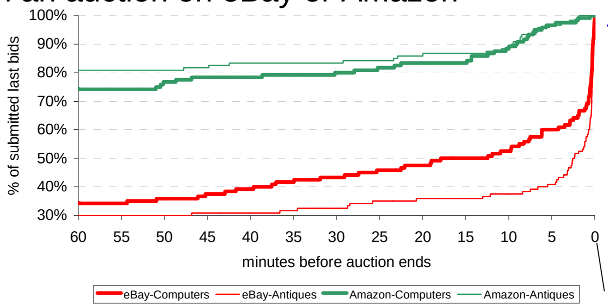
A natural experiment on ending-rules – Roth and Ockenfels' (2002) hypotheses

TABLE 1—HYPOTHESES ABOUT THE CAUSES OF LATE BIDDING

Hypotheses	Predicted contribution to late bidding
Strategic hypotheses	
Rational response to naïve English-auction behavior or to shill bidders: bidders bid late to avoid bidding wars with incremental bidders	All three strategic hypotheses suggest more late bidding on eBay than on Amazon, with a bigger effect for more experienced bidders. Also (via the third point), more late bidding in categories in which expertise is important than in categories in which it is not.
Collusive equilibrium: bidders bid late to avoid bidding wars with other like-minded bidders	
Informed bidders protecting their information (e.g., late bidding by experts/dealers)	
Nonstrategic hypotheses	
Procrastination	No difference between eBay and Amazon.
Search engines present soon-to-expire auctions first	
Desire to retain flexibility to bid on other auctions offering the same item	
Bidders remain unaware of the proxy bidding system	
Increase in the willingness to pay over time (e.g., caused by an endowment effect)	
Bidders do not like to leave bids "hanging"	

Ending-rules and sniping

Cumulative probability distributions of the timing of the last bid in an auction on eBay or Amazon



Share of bids

	eBay	Am.
Last hour	68%	23%
10 min	55%	11%
5 min	50%	3%
1 min	37%	.4%
10 sec	12%	0%

Amazon: "original end-time "

More sniping on eBay than on Amazon.
More sniping in Antiques than in Computers (experience!).
Experienced bidders bid later on eBay, but earlier on Amazon.
Sniping has strategic reasons, as hypothesized.

A lab experiment on ending-rules

The field study of Roth and Ockenfels (2002) may have been confounded by the following factors:

- Interpretation of such field data is complicated by the fact that there are differences between eBay and Amazon other than their ending rules:
- eBay has many more items for sale than Amazon, and many more bidders.
- Buyers and sellers themselves decide in which auctions to participate, so there may be differences between the characteristics of sellers and buyers and among the objects that are offered for sale on eBay and Amazon.
- Some combination of these uncontrolled differences between eBay and Amazon might in fact be the cause of the observed difference in bidding behavior, instead of the differences in rules.

A lab experiment on ending-rules

Some further problems and possible confounds:

- "Feedback ratings" used as proxies for experience may be imperfect. For example, feedback ratings only reflect the number of completed transactions, but not auctions in which the bidder was not the highest bidder.

- In addition, more experienced buyers on eBay may not only have more experience with the strategic aspects of the auction, they may have other differences from new bidders, e.g., they may also have more expertise concerning the goods for sale, they may have lower opportunity cost of time and thus can spend the time to implement a snipe, or they may be more willing to pay for the fixed cost of purchasing a sniping program.

Ariely, Ockenfels and Roth (2005)

- They report an experiment on second-price auctions that differ only in the rule for how the auctions end.
- Subjects are randomly assigned to each auction type, so there are no systematic differences in bidder characteristics across auctions (*no self-selection!*), and the number of bidders per auction is kept constant (*c.p.*).
- Each bidder in the experiment participates in a sequence of auctions, allowing Ariely et al. (2005) to observe in detail how bidding changes as bidders gain experience with the auction environment (*control for experience*).
- The goods offered in the auctions are artificial, independent private-value commodities.

Ariely et al. (2005) – Design

- 2 bidders in each auction.
- Private value for each bidder from uniform distribution {6$, 10$}.
- Second-price auction.
- Profit = private valuation – price + increment 0.25$ (for winners).

- All auctions were run in discrete time, so that we can precisely define 'bidding late' without running into problems of continuous time decision making such as individual differences in typing speed, which might differentially effect how late some bidders can bid.

Ariely et al. (2005) – Treatments

eBay.8

- Stage 1 (early bidding). Discrete periods. Bidders can submit bids in each period. As soon as no bid is submitted in a period, stage 1 ends.
- Stage 2 (late bidding). Both bidders can submit a final bid, but this bid is transmitted only with probability 80%.
- After stage 2, the auction ends.

eBay1

- Like eBay.8, but stage 2-bids are transmitted in all cases (100%). I.e., no risk of late bidding.

Ariely et al. (2005) – Treatments

Amazon

- Stage 1 like in eBay.8.
- Stage 2 also like in eBay.8. However, if any bid is transmitted successfully (80%), then the auction returns to stage 1 and bidding continues.
- Hence, Amazon has same risk of late bidding as eBay.8, but a successful bid extends the auction.

Sealed bid

- There is no stage 1 in this treatment, but only a stage 2 where bidders can make one bid which is transmitted with 100% probability.

Ariely et al. (2005) – Summary of treatments

TABLE 1 Experimental Treatments

Auction Condition	Number of Stage-1 Periods	Number of Stage-2 Periods	Probability of Stage-2 Bid To Be Successfully Transmitted
Amazon	Endogenous	Endogenous	80%
eBay.8	Endogenous	1	80%
eBay1	Endogenous	1	100%
Sealed bid	0	1	100%

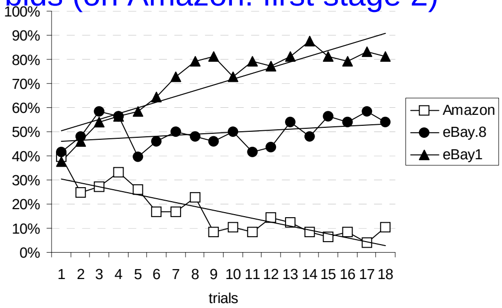
Ariely et al. (2005) – Some hypotheses

- Bids above the private valuation should not occur.
- Stage 2-bids in eBay should approach the private valuation ("approach" only because of the increment).
- The same is not expected in Amazon where incremental bidding may be an equilibrium (because subjects have a chance to improve their bids later).
- There is more sniping in eBay.8 than in Amazon.

Ariely et al. (2005) – Results

- The Figure shows that the experimental results reproduce the main internet observations:
- There is more late bidding in the fixed-deadline (eBay) conditions than in the automatic extension (Amazon) condition.

Percentage of bidders with stage-2 bids (on Amazon: first stage 2)

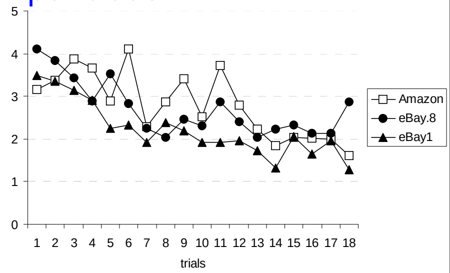


- As bidders gain experience, they are more likely to bid late in the eBay conditions, and less likely to bid late in the Amazon condition.

Ariely et al. (2005) – Results

- The rise in stage-2 bidding in the two eBay conditions is not part of a general increase in bidding activity, but just the opposite: the number of stage-1 bids is strongly decreasing in all three multi-period auctions.

Number of stage-1 bids per bidder



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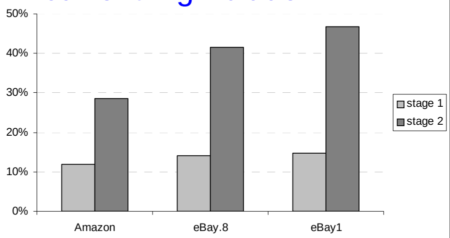
Ariely et al. (2005) – Results

- This Figure shows that stage-1 bids are rarely placed by the current high bidder; early bids are mostly made in incremental bidding wars, when the low bidder raises his bid in an apparent attempt to gain the high bidder status.

Share of bids submitted by current high bidder



- On the other hand, stage-2 bids in the eBay conditions are made almost equally often by the current high bidder and the current low bidder.
- That is, late bids on eBay appear to be planned by bidders regardless of their status at the end of stage 1.

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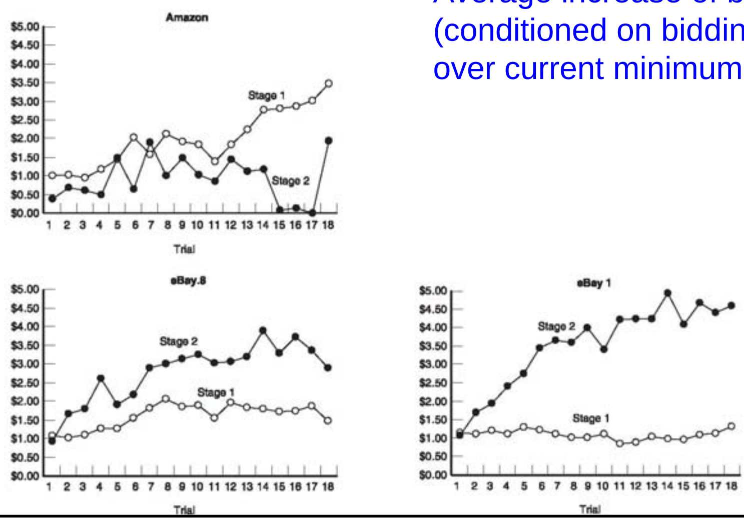
Ariely et al. (2005) – Results

FIGURE 3
AVERAGE INCREASE OF BIDS (CONDITIONED ON BIDDING) OVER CURRENT MINIMUM BID



Average increase of bids (conditioned on bidding) over current minimum bid

Ariely et al. (2005) – Results

Average increase of bids (see previous slide)

- The average stage-2 increment is about twice the size of the stage-1 increments on eBay.8, and four times the size on eBay1, while it is only about half the size of stage-1 increments on Amazon.

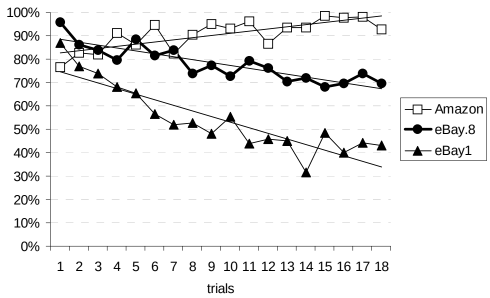
- That is, as late bids become less frequent on Amazon they also become smaller, and as they become more frequent on eBay they also become larger. Thus, on eBay most of the 'serious' bidding is done in stage 2, while on Amazon most of the serious bidding is done in stage 1.

Ariely et al. (2005) – Results

- The pattern of early and late bidding affects price discovery, i.e., how well the price in stage 1 predicts the final price.

- This figure shows that stage 1 prices are an increasingly good predictor for final prices on Amazon whereas the opposite is true on eBay.8 and eBay1.

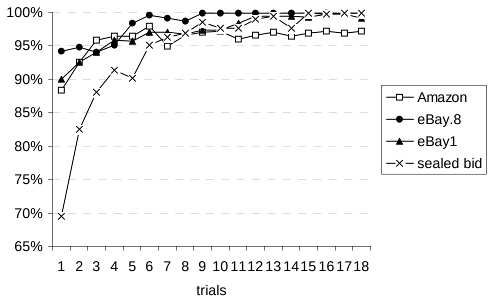
Final stage-1 price (on Amazon: first stage 1) as percentage of final price and linear trends



Ariely et al. (2005) – Results

- The median of final bids relative to values is increasing over time, but never exceeds 100 percent.
- Up to trial 7, final bids in the sealed bid condition are substantially lower than final bids in the other conditions.
- It appears that learning in the sealed bid auctions takes place across auctions, while learning in the dynamic auctions also takes place within auctions.

Median of final bids (including lost stage-2 bids) as a percentage of value



Ariely et al. (2005) – Results

Learning

- A bidder who imagines that he can win with a low bid does not learn that he is mistaken in a sealed bid auction until after the auction is over.
- But in the auctions conducted over time, he can revise his bid as soon as he is outbid.
- Incremental bidders learn on eBay that they are sometimes outbid in stage 2 at prices more than an increment below values, which conceivably leads them to bid closer to values over time.
- Incremental bidders on Amazon, on the other hand, are never outbid at prices more than an increment below their values, regardless of how their final bids relate to the values.
- Thus, for incremental bidders, the pressure to learn to bid one's value is weaker on Amazon than on eBay. Once incremental bidding has reached the second highest value, the high value bidder has no incentive to bid up to his own value.

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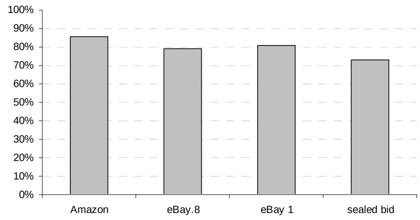
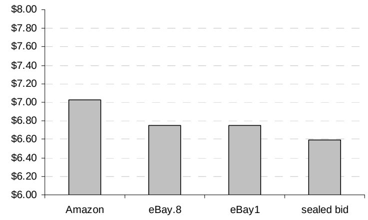
Ariely et al. (2005) – Results

- The Amazon condition is slightly more efficient and yields higher revenues than the other conditions.
- This seems to reflect that Amazon is the only treatment where low bidders can always respond to being outbid at prices below values, while eBay-bidders could only respond to stage-1 bids but not to stage-2 bids, and losers in sealed bid never had the opportunity to respond to the bids of other bidders.



Average efficiency



Median revenues

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Ariely et al. (2005) – Final thoughts

- Institutional details matter!
- While the results of the experiment replicate the basic observations in the field data, we do not claim that the field data are fully explained by the experimental data.
- Yet, by design, the experimental setting eliminated some complicating strategic factors as well as sources of variation across internet auction sites.
- By eliminating these factors, the experiment showed that they are neither necessary to produce sniping on eBay nor to produce the observed differences between eBay and Amazon: the rules for ending these auctions drive the bidding dynamics.
- Experimental and field data, together with the theory developed to explain them, are complements, not substitutes.

More on Internet auctions – The role of feedback mechanisms

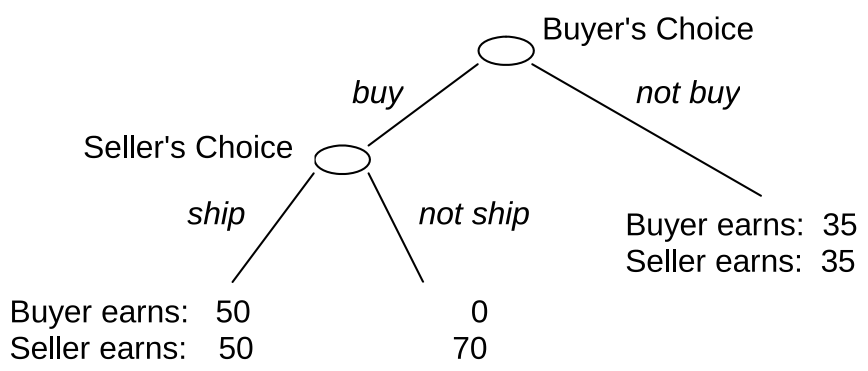
Having examined the role of auction rules for bidding behavior (both timing and size of bids), we pause for a moment to study why commerce on Internet auction-platforms works at all.

Given the anonymity of bidders it seems an interesting question how trust among the involved parties can be fostered to reap the possible efficiency gains.

A paper by Bolton et al. (2004) addresses this question.

(Note that this is not an auction-paper, but it is closely related to Internet auctions.)

Bolton, Katok and Ockenfels (2004) – The buyer-seller encounter



Bolton et al. (2004) – Treatments

REPUTATION

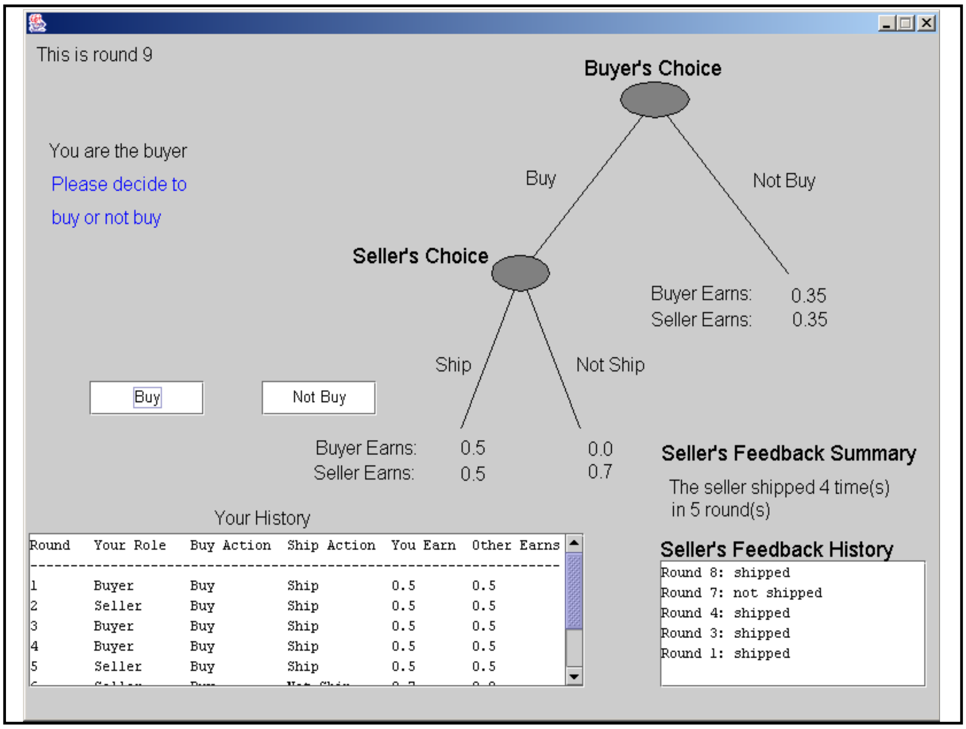
- Random pairing. Buyer is given feedback on the seller.

STRANGERS

- Random pairing. No feedback about one another's history.

PARTNERS

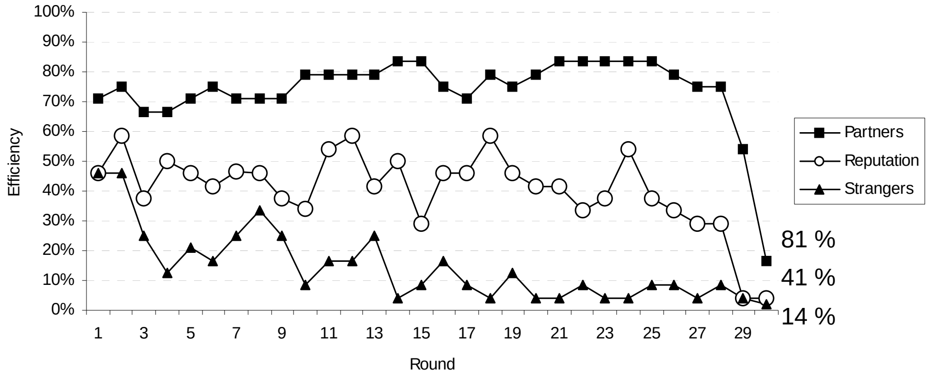
- Fixed pairing. Same feedback as available in Reputation.



Bolton et al. (2004) – Procedure

- Each market has 3 sessions.
- 16 subjects per session (48 per market) for a total of 144 participants.
- Subjects are half the time buyers, half sellers; otherwise random.
- All rules and payoffs of the game and all procedures are public knowledge.
- Each subject is paid his or her earnings in cash plus a $5 show-up fee.

Bolton et al. (2004) – Results



Efficiency measured as the relative frequency of trade (buy).
Partners > Reputation > Strangers

Bolton et al. (2004) – Results

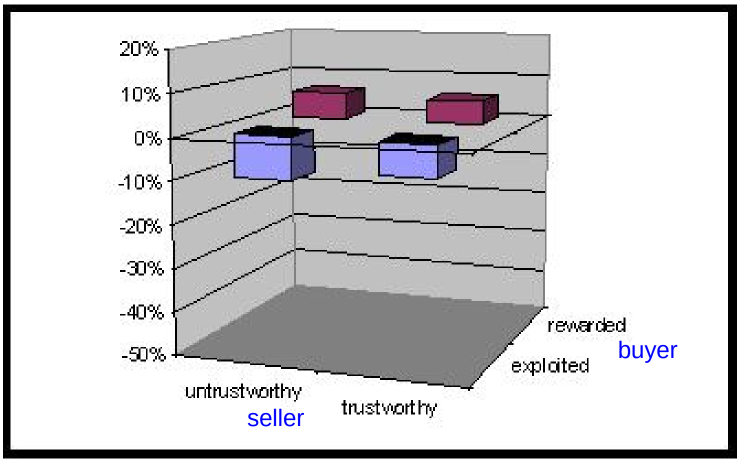
- More trustworthiness in Reputation (73 percent) than in Strangers (36 percent).
- Endgame effect in Reputation but not in Strangers.
- Positive correlation between payoffs and frequency of buying/shipping in the Reputation market, while the opposite is true in the Strangers market.

Why is there a role of matching … when reputation is available?

- Information flows in Reputation markets create external benefits of both trust and trustworthiness
- … that are internalized in Partners relationships.
- The following slides show why:

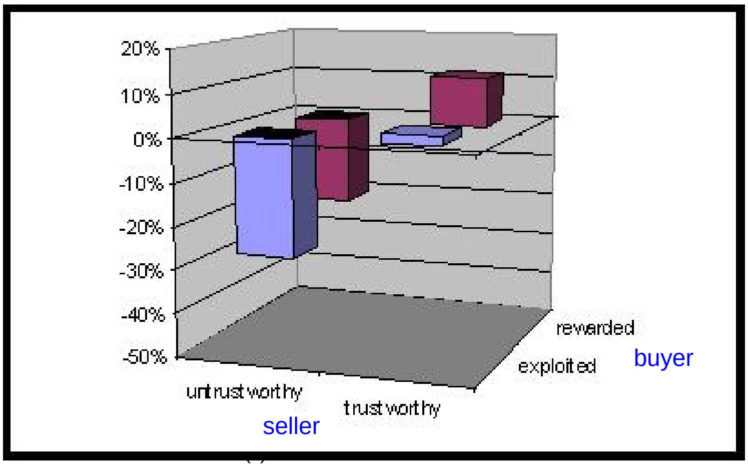
Trust in Strangers …

Marginal effects on likelihood of “buy” in strangers (average buy = 37.1%)



Trust in Reputation …

Marginal effects on likelihood of "buy" in Reputation (average buy = 55.6%)



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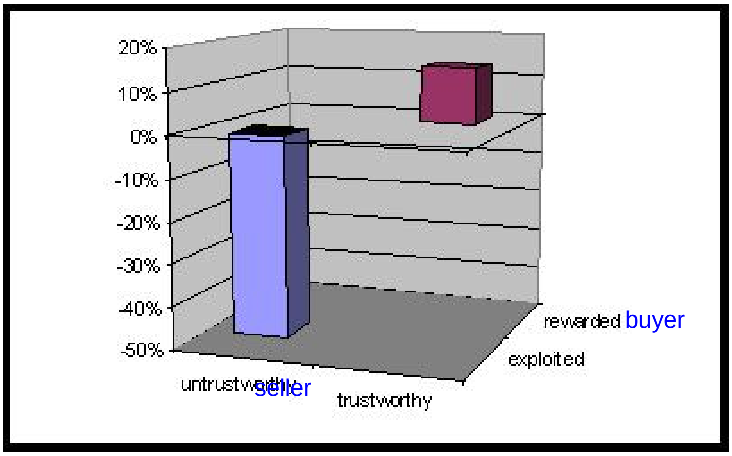
Trust in Partners …

Marginal effects on likelihood of "buy" in Partners (average buy = 83.3%)



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Reputation and matching

- Buyer trust is a function of the seller's reputation *and* one's own experience.
- Thus, trustworthiness has two positive effects on trade - via the feedback and via the experience channel.
- The experience channel effect is not internalized in Reputation. Hence the higher efficiency in Partners.

Reputation and matching

- A trusting buyer in a Reputation market generates valuable feedback information for *other* buyers.
- Example from the Reputation market: On average …
  - buying from a newby yielded a loss.
  - buying from a trustworthy seller yielded a profit.
- So, in Reputation markets, everybody is interested to have feedback information, but nobody should be interested in generating it.
- This external effect of information generation is internalized in Partners markets (there, if you don't trust a newby, you never trust).

Experiments on 3G/UMTS-Auctions

In the late 1990ies many European countries prepared for auctioning off spectrum licences for third generation (also called UMTS) mobile telecommunication services.

The U.K. was the first country to prepare – and ultimately implement – such an auction.

The British Radiocommunications Agency (RA) commissioned a series of experiments (principal investigator: Ken Binmore) to study the "optimal" auction format ("optimal" with respect to competition, new entrants, fiscal revenues, …).

Experiments on 3G/UMTS-Auctions

Among the foremost questions to be prepared was the auction format. The RA first favored a hybrid Anglo-Dutch auction format, which consists of an ascending English auction in a first stage (to limit the number of bidders to the number of licences plus one) and a sealed-bid auction in the second stage.

Two forms of the sealed-bid auction were considered:

1) A discriminatory auction where the winners pay their actual bid.
2) A uniform auction where all winners bid the lowest winning bid.

Experiments on 3G/UMTS-Auctions

Potential bidders could comment on the auction design and format.

To do so, one potential bidder commissioned Reinhard Selten and a team of collaborators to study the economic effects of the two proposed auction formats (as well as their difference to a standard ascending English auction that dispenses with a second stage sealed-bid auction).

The paper by Abbink et al. (2005) is the outcome of this commissioned report.

A remark on the valuation model

Most auctions use one of the following two valuation models for bidders:

1) Private values. Each bidder has a private valuation for the good, without knowing the other bidders' valuation.
2) Common values. The value of the item is the same for all bidders, but unknown at the time of the auction.

The 3G/UMTS-auctions are best represented by a mix of both models.

A) Common value component (development of market)
B) Private value component (incumbency advantages).

Abbink, Irlenbusch, Pezanis-Christou, Rockenbach, Sadrieh, Selten (2005)

Valuation of bidders consists of

- Common value component (cvc) from the interval [1000, 1500]. cvc is identical for all bidders, but each bidder only receives a private signal about the cvc by a uniform random draw from the interval [cvc – 200, cvc + 200]. This signal shall be called the estimated common value component (ecvc).
- Private value component (pvc). A uniform random draw from the interval [-100, +100], with two types of bidders.
  * INC (incumbents). 80% chance for draw from [0, +100], 20% chance for draw from [-100, 0].
  * NEW (newcomers). 80% chance for [-100, 0], 20% chance for [0, +100].

Abbink et al. (2005) – Treatments

- 8 bidders, 4 of type INC, 4 of type NEW.
- 4 licences
- 3 treatments
  - A) Discriminatory Anglo-Dutch auction with 2 stages.
  - B) Uniform Anglo-Dutch auction with 2 stages.
  - C) English auction with one stage.
- 15 auctions in each treatment.
- 184 participants (some inexperienced, some experienced).
- Run in 1998 in Bonn.

Abbink et al. (2005) – Stage 1

Stage 1. Multiple bidding rounds to reduce number of bidders to 5 (in Anglo-Dutch auctions) or to 4 (in English auction).

Bidding starts with reserve price. Depending upon the number of bidders in the auction increments to the sixth (fifth) highest bid from previous round.

Table 1
Bidding increments

Number of active bidders	Current price (c)	Increment
8	$c =$ reserve price (r)	+175
	$r + 1 \leqslant c \leqslant r + 175$	+125
	$r + 176 \leqslant c \leqslant r + 300$	+75
	$c > r + 300$	+25
7	Always	+20
6	Always	+10

Abbink et al. (2005) – Stage 2

Stage 2 (in Anglo-Dutch auction). 5 bidders submit sealed bid. The four highest bidder get a licence and pay the following amounts.

Discriminatory auction. Each bidder pays his bid.

Uniform auction. Each bidder pays lowest winning bid.

The English-auction treatment ends in stage 1 when four bidders have quit the auction. The four winning bidders pay the fifth highest bid from the previous period (i.e. the highest losing bid).

Abbink et al. (2005) – Efficiency

Efficiency is measured as the total surplus generated in the auction (i.e. the sum of valuations of successful bidders).

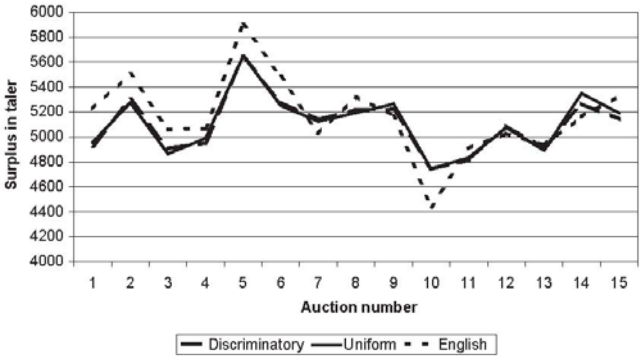

Fig. 1. Average total surplus - inexperienced subjects.

No significant differences in efficiency between treatments.

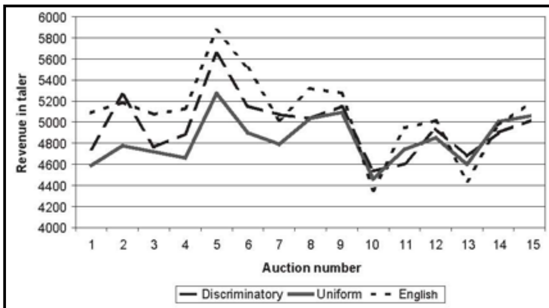

Fig. 3. Average revenue - inexperienced subjects.

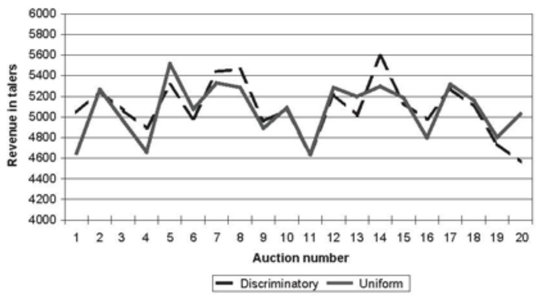

Fig. 4. Average revenue - experienced subjects.

Revenues

… defined as the prices paid by the successful bidders.

English auction has highest revenues due to aggressive bidding. Discriminatory auction has on average higher revenues (winner's curse!) than uniform auction (with inexperienced traders). However, with experience the latter difference vanishes completely.

Abbink et al. (2005) – Summary

The three different auction formats basically yield the same results with respect to efficiency, revenues, chances for new entrants, or winner's curse.

This holds in particular true for the later rounds of the experiment, where even inexperienced bidders have acquired some experience.

Due to the similarity of behavior across the three different auction formats, the following paper by Sutter et al. (2007) has only considered the English auction format.

UMTS-auctions and team bidding

In the backoffice of companies bidding for a 3G/UMTS licence there were often (if not always) expert teams to give advice on how to bid.

Even though an actual bid had to be submitted by an authorized company representative, it seems natural to assume that bids were influenced by team decision-making.

Sutter et al. (2007) address the influence of team-bidding on behavior in an UMTS-type auction.

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SS1 For more details: see Design which I wil present in a few minutes.
Sabine Strauß, 13.Apr.04

Sutter, Kocher and Strauß (2007) – Design

- 4 bidders (2 INC, 2 NEW) and 2 licences
- 15 English auctions with multiple bidding rounds and increments like shown below.
- Auction ended when 2 bidders quit.

Table 1: Bidding increments

Increment	Condition	Number of bidders active in auction
100	Minimum bid[†] in current round ≤ minimum bid in previous round + 150	4
50	Minimum bid in current round > minimum bid in previous round + 150	4
25	always	3

[†] The minimum bid in the current round is determined as the third highest bid of the preceding round, plus the increment.

Sutter et al. (2007) – Treatments

The 4 bidders were either

- INDIVIDUALS, or
- TEAMS, where teams consisted of three members who had to agree on the team‘s bid (face-to-face communication).

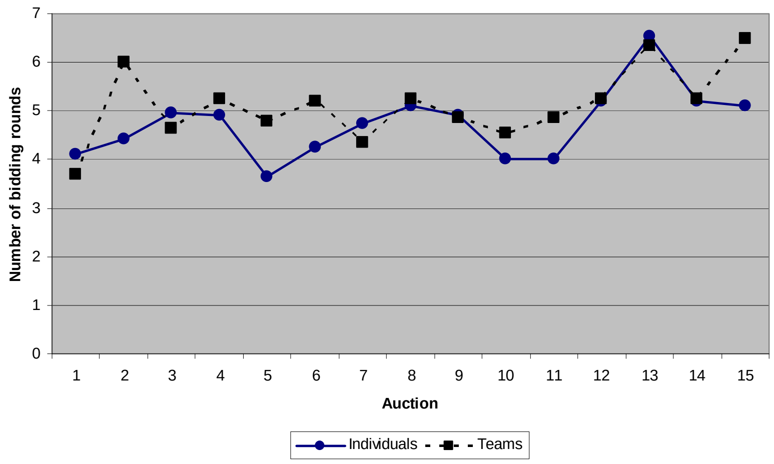
Per capita incentives were kept constant.

The same 10 set-ups (of random draws of cvc and pvc → same structure as in Abbink et al., 2005) were used in both treatments.

160 participants (40 in INDIVIDUALS, 120 in TEAMS).

Sutter et al. (2007) – Results

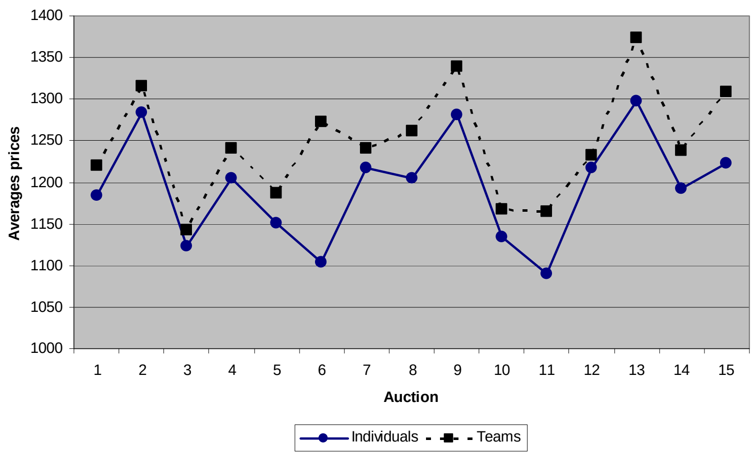
Figure 1. Average number of bidding rounds



Teams stay longer in the auction, but not significantly so.

Sutter et al. (2007) – Results

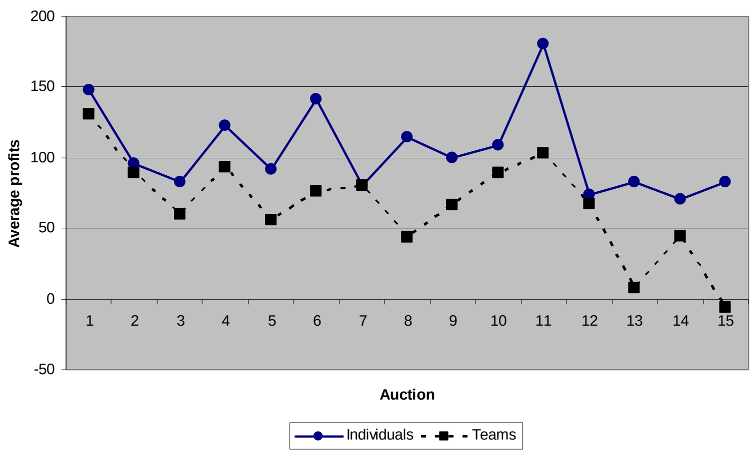
Figure 2. Average prices



Teams pay significantly higher prices (by about 4.3%).

Sutter et al. (2007) – Results

Figure 3. Average profits



Teams earn significantly lower profits.

Sutter et al. (2007) – Further results

On average, teams suffer from the winner's curse more often than individuals, however not significantly so.

The allocation of licences is significantly more efficient in TEAMS than in INDIVIDUALS. Whereas 71% of licences are awarded in TEAMS to the two teams with the highest actual valuation, this happens in only 64% of cases in INDIVIDUALS.