AN EXPERIMENTAL COMPARISON OF FIRST- AND SECOND-PRICE AUCTIONS - THE CASE OF TRACK CAPACITY ALLOCATION

Gunnar Isacsson* and Jan-Eric Nilsson**
Centre for Research on Transportation and Society, Dalarna University, S-781 88 Borlänge, Sweden

1. INTRODUCTION

The background of the present paper is the recent organisational restructuring of the Swedish railway sector. A central aspect of this restructuring is the separation of infrastructure management from train operations. From 1988, the National Rail Administration is in charge of railway infrastructure while the Swedish State Railways (SJ) operates trains. The government has subsequently introduced competition between operators over the state-owned infrastructure, much in the same way as private cars, busses and trucks make use of publicly provided road infrastructure. Subject to some restrictions, it is possible for entrants to operate freight (while not passenger) services from July, 1996. Nilsson (1995) has more detail on this issue.

One crucial feature of the deregulation concerns the method to realise timetables when there are multiple train operators. At present, a timetable is created annually on the basis of internal SJ discussions, SJ being the (almost) single operator. A classification of trains into different priority classes is a key instrument to make trade-offs in situations where demand exceeds supply of track capacity. Our conjecture is that it might prove difficult to realise an efficient timetable, i.e. a schedule that is able to maximise the social value of capacity use, by way of discussions when there are multiple and possibly competing users of railway track. In the present paper we therefore turn our attention to four different market mechanisms or auctions as candidate tools for solving the problem of creating a timetable, or in other words allocating the right to use railway tracks.

Most people are acquainted with auctions where single units of a well-defined good is sold. This might lead some people to dismiss the idea of using an auction for allocating such a complex good as the right to use railway tracks as too unrealistic. However, there are several recent cases where it has been suggested that more complex goods can be sold in auctions. Examples include radio frequencies (McAffee & McMillan 1996), airport slots (Rassenti, Smith & Bulfin 1982), the right to use pipelines in a network for the transportation of gas (McCabe, Rassenti & Smith 1989) and space in the NASA earth orbiting station (Banks, Ledyard & Porter 1989). At least one of these examples has been implemented. Hence, it is not *per se* unrealistic to allocate complex goods in this way. The issue is rather in which way the allocation mechanism should be designed.

Much of the research that has been done on the above auctions has used experiments as test-beds for the development of the auctions. This amounts to a type of demonstration of how an auction or market mechanism works in solving a given allocation problem (cf. Plott 1994). The

* Tel. +46 23 77 85 43, Fax. +46 23 77 85 01, e-mail. gis@cts.du.se
** Tel. +46 23 77 85 48, Fax. +46 23 77 85 01, e-mail. jen@cts.du.se

allocation problems used in the experiments are usually simplified in many respects but contain some relevant features of the allocation problem found in the real world. The idea is that if a mechanism can not solve the simplified allocation problem in the experiment, it will probably not be able to solve the more complex real world problem. Hence, the mechanism can be rejected as a candidate tool for solving the allocation problem, or at least it has to be modified. On the other hand, if the mechanism performs well in the simplified environment more complexity can be added and additional experiments can be conducted. This process is likely to produce insights regarding what aspects of a given allocation problem that are potentially problematic to a market mechanism and how the mechanism can be changed accordingly.

In this paper we report the results from a series of testbed-type experiments of four different mechanisms to sell the right to use railroad tracks. These are (i) a first price ascending auction, (ii) a first price one-shot auction, (iii) a second price ascending auction and (iv) a second price one-shot auction. The questions that we address are the following. Can we reject the idea of using an auction to allocate efficiently the right to use railroad tracks? Which one, out of four proposed auctions, leads to the most efficient allocations? Is the observed bidding behaviour consistent with the one that theory predicts whenever such predictions exist?

The reason for testing these four auctions is that the results from previous work on track capacity auctions indicate that the behaviour of individuals produce efficient outcomes under both a first- and a second-price ascending auction (cf. Brewer & Plott 1996 and Nilsson 1996, respectively). In the present paper both pricing principles are compared under two alternative stopping rules in a unified experimental framework to see if one is superior to the other.

The paper is organised as follows. Section 2 outlines the environment of the track allocation problem and states the problem formally. We describe the mechanisms to be tested experimentally in section 3. The experimental design is presented in section 4 and the results from the experiments in section 5. Section 6 concludes with a discussion of the results.

2. BASIC CONCEPTS OF THE TRACK ALLOCATION PROBLEM

We claimed in the introduction that one distinguishing aspect of the track allocation problem is related to the complexity of this good. Section 2.1 is therefore used to clarify three aspects of this complexity. We refer to this as the 'environment'. Section 2.2 presents the track capacity allocation problem for this environment.

2.1 The Environment

By "environment" we shall in the following mean (i) a set of departures-arrivals for a given block, which is the shortest line segment in a railway network that can hold one train at a time during a specific time interval, (ii) the valuations of the different train operators for each and every departure option in the given time interval and (iii) the set of departures-arrivals that are technically admissible in the time interval under consideration.

Thus, we focus on one block between the geographical positions x and y which are two different nodes in a railway network.[1] Furthermore, let us pinpoint a time interval $[t_-, t^-]$ with $t_- < t^-$

[1] Nilsson (1996) argues why the concentration on a single block may not be very restrictive.

such that there is no train that departs earlier than t_- from x or y *and* arrives at y or x later than t_-. The upper limit of the time interval, t^*, is defined correspondingly. A 'departure-arrival' is a specified time interval $[t_d, t_a]$ where t_d denotes the time of departure and t_a the time of arrival, $t_d < t_a$, such that $[t_d, t_a] \subset [t_-, t^*]$. In what follows we speak of 'departures' for short.

The set of departures from x to y for which the operator has a positive willingness to pay in the time interval under consideration is denoted by Ω_{xj}, i.e. $t_{xij} = [t_d, t_a]_{xij} \in \Omega_{xj}$, $i = 1, 2, \ldots, T_j$. The set Ω_{yj} is defined similarly, i.e. $t_{yij} = [t_d, t_a]_{yij} \in \Omega_{yj}$, $i = 1, 2, \ldots, T_j$. Obviously, T_j might vary between different train operators.

The number of operators who want to run trains from x to y is denoted by N_x and N_y is the number of train operators who want to run a train in the opposite direction. Assume that the valuations of each train operator, j ($j = 1, 2, \ldots, N_x$) for each t_{xij} is a real valued function, f_j: $\Omega_{xj} \rightarrow \Re_{++}$. Similarly, the valuations of each train operator, j ($j = 1, 2, \ldots, N_y$) for each t_{yij} is a real valued function, f_j: $\Omega_{yj} \rightarrow \Re_{++}$. Let $v_{xij} = f_j(t_{xij})$ and $v_{yij} = f_j(t_{yij})$. Each f_j is assumed to be private information held by operator j. We also assume that each train operator demands one single out of possibly several alternative departures in the given time interval. Finally, let $f = \{f_1, f_2, \ldots, f_{Nx}, f_1, f_2, \ldots, f_{Ny}\}$ and $\Omega = \{\Omega_{x1}, \Omega_{x2}, \ldots, \Omega_{xNx}, \Omega_{y1}, \Omega_{y2}, \ldots, \Omega_{yNy}\}$.

Suppressing the index for x and y and the index denoting the number of the specific train operator, two different departures, t_i and t_k, are said to be technically admissible if there is no point in t_i which is also a point of t_k. In other words, two trains are technically admissible if they are not using the tracks between x and y at the same time. Still focusing on the time interval $[t_-, t^*]$, we can define a set of admissible departures in this time interval as a set of departures whose intersection is the empty set, ϕ_i. That is,

$$\phi_i = \{t_k: t_i \cap t_k = \varnothing \text{ and } t_i, t_k \subset [t_-, t^*], k = 1, 2, \ldots, i-1, i+1, \ldots, M\},$$

$$i = 1, 2, \ldots, M \text{ where } M = \sum_{j=1}^{N_x+N_y} T_j .$$

Furthermore, the set of all ϕ_i is denoted Φ^A. To summarise, an environment, E, is defined by the set of all departures between x and y (Ω), the operator's value functions (f) and the set of technically admissible departures (Φ^A), i.e. $E = \{\Omega, f, \Phi^A\}$.

2.2 The Allocation Problem

Given this simplified definition of an environment, the problem to allocate track capacity is to establish an allocation that is Pareto efficient in the sense that there is no other allocation that would generate a higher total gross surplus to the group of train operators. In other words, the objective is to select that allocation that yields the highest maximum surplus. This is subject to three restrictions. The first restriction is simply that the departures must belong to the set of departures under consideration. The second restriction is that the allocation has to belong to the set of admissible allocations, Φ^A. The last restriction is that each train operator shall at most be allocated one departure in the time interval under consideration. The allocation that solves this problem results in a "time-table" for the given block.

This problem can be analytically handled as a so called assignment problem (cf. Koopmans & Beckman 1957 and Olson & Porter 1994 for experimental evidence on auctions designed for solving this problem). The (linear) assignment problem deals with the problem of "matching two sets of an equal number n of objects, by making up pairs of objects consisting of one object from each set." (Koopmans & Beckman 1957, p 54). The objects in one of the sets - the agents - are assumed to 'have preferences' over the (indivisible) objects in the other set. 'The problem is to find a matching (...) of objects for which the sum of scores of pairs matched is as high as possible.' (Ibid.)

Matching students to an available supply of student rooms is one example of this problem. The track allocation problem consists also of two sets of objects from which we shall make pairs. These are the set of train operators and the set of departures. Thus, at an intuitive level the two problems are similar.

However, there are two features that make the problems dissimilar. First, the number of operators is not necessarily equal to the number of departures. To equalise the number of objects in each set, a number of fictitious objects can be included in the set that contains the lower number of elements. For example, if the number of operators (n) are larger than the number of departures (k) we simply include n-k objects in the set of departures which all correspond to fictitious departures. Every operator is assumed to have a zero value for being assigned such a fictitious departure.

Second, different operators may ask for a different number of departures. To deal with this we turn to the set of feasible solutions, Φ^A. Note, first, that in the track allocation problem any feasible solution is characterised by a matching of operators to departures (including fictitious operators or departures). Second, let v_{ki} denote the value if object k in the first set is assigned to object i in the second set. Then note that the assignment problem can be understood as a search for a permutation matrix $\hat{P} = [\hat{p}_{ki}]$, k, i = 1, 2, ..., n of which each row and each column contains a single element which is equal to 1, while all other elements are equal to 0. This matrix is such that $\sum_k \sum_i v_{ki} p_{ki} \leq \sum_k \sum_i v_{ki} \hat{p}_{ki}$ for all permutation matrices $P = [p_{ki}]$ (see Koopmans & Beckman 1957, p. 55).

However, an equivalent way of establishing a solution to this problem is simply to first compute the sum of the values for every admissible assignment (one object from the first set to every object in the other set) and then select the assignment with the highest value. In the terminology of the track allocation problem, this would simply mean that we compute the value of every admissible allocation and then pick the allocation with the highest value.

Thus, the problem of finding a solution to the track allocation problem is equivalent to the problem of finding a solution to the assignment problem in spite of this second difference between the two problems. This conclusion means that we can now rely on previous analyses of the generic assignment problem and the auctions designed for solving this allocation problem in order to predict individual bidding behaviour.

3. THE MECHANISMS

Given knowledge of f, the problem to allocate track capacity to different train operators is possible to solve. However, since f_j is assumed to be private information held by each train operator, j, we need some mechanism that guarantees that train operators submit messages such that we obtain the value maximising solution to the allocation problem on the basis of these messages. We will consider four mechanisms and test if they have this property.

An auction or mechanism is, more precisely, defined to be (i) a set containing the bid space of the operators, (ii) a function that transforms bids into proposed allocations and prices and (iii) a rule which determines when a final allocation and set of prices is reached. Independent of which auction is used, an allocation is determined as the solution to the allocation problem presented in section 2.2. However, instead of the true values the submitted bids are used to determine this allocation.

In the first price auctions each operator has to pay a price equal to the bid that was submitted on the departure that is allocated to that operator. If no departure is allocated to an operator he/she does not have to pay anything. To determine the price that an operator j has to pay in the second price auctions for departure x_i, we follow the following four steps. (i) Compute the total value of the allocation (V^*) in terms of the submitted bids. (ii) Subtract the bid submitted by operator j on the departure that was allocated to him/her, b_{xij}, from V^* This gives us the value of the allocation to all operators but operator j in terms of the submitted bids. (iii) Delete the vector of all bids submitted by operator j and determine a new value-maximising allocation on the basis of the remaining bid vectors. Then compute the total value of this second allocation, V^{**}. (iv) The price, p_{xij}, that operator j has to pay for being allocated departure, i, is simply the difference between these two values, i.e. $p_{xij} = V^{**} - (V^* - b_{xij})$.

We also consider two alternative stopping-rules for each of the two pricing rules. A stopping-rule determines when a final allocation and set of prices are reached. The first rule stipulates that allocations and prices are determined by the first set of bids, i.e. one-shot bidding. The second stipulates that bidders are allowed to raise their bids successively until no bidder wants to raise their bids any further, i.e. an ascending bidding procedure.

The pricing principle in the second price auction is identical to the pricing principle suggested by Leonard (1983) as a tool for solving the assignment problem. He also shows that it is incentive compatible to bid the true values under this pricing rule. Thus, given the correspondence between the track allocation problem and the generic assignment problem, a prediction of the bidding behaviour under this pricing principle is that the bidders will bid their true valuations for the departures.

Demange, Gale & Sotomayor (1986) consider an ascending first price auction for the same problem. However, since the first price auctions that we implement differ somewhat to theirs, we can only conjecture that it is optimal for an operator to bid as follows. (i) Do not bid higher than the value of a departure. (ii) Always bid a pivotal bid if such a bid exists. A pivotal bid is a bid that changes the allocation and increase the operators profit should the auction end immediately after that bid has been submitted (the terminology is picked from the classification scheme of bids suggested by Brewer & Plott 1996).

4.THE EXPERIMENTS

To test which one of the four mechanisms that produces the 'best' allocations we use the by now standard experimental technique of inducing redemption values for all bidders over each of their departures. Since we as experimenters have control over 'true' values, it is possible to determine the optimal allocation and compute the value of this allocation. Given a realised allocation in the experiment we can also compute the value of this allocation. The 'allocative capacity' of each mechanism can then be determined by comparing the value of the realised allocation to the optimal one. This section begins with an outline of the specific features of the environments that we have used (section 4.1). Then we present the experiments in terms of subject characteristics, training and variations in the experimental treatments of different groups (section 4.2).

4.1 Experimental Environments

To clarify those aspects of the allocation problem that we want to adress, we shall use a so-called string diagram to represent an environment. A string diagram depicts consecutive nodes by horizontal lines while moves along these lines represent time. A departure is represented by a string from one node in the network to another (cf. figure 1). Speed is implicitly defined by the tilt of the string, i.e. the faster is the train, the steeper is the string. Strings *B, B, B* and F represent trains from node x to node y while strings *A, A, A*, C, D and E represent trains in the other direction. The figure is also useful to depict allocations that are not admissible in that strings crossing between the nodes indicate that two trains travelling in opposite direction collide, or that a faster train catch up a slower.

Using these stylised types of interactions between departures, experiments have confronted subjects with situations referred to as type I, type II and type III conflicts. These represent aspects of the generic track allocation problem that we want to address in our testbed.

Type I conflicts. The first aspect stems from our belief that a significant feature of this problem is that one 'most preferred' use of tracks has a large number of alternative, close substitutes in time. For example, a train operator who prefers to leave with a train from point x at time 7:00 to arrive at point y at time 8:00 may have alternatives to this departure. She could, for instance, leave x at 7:05 to arrive at y at 8:05. Thus, if there is some other operator who wants to use the track between x and y during (parts of) the same period of time this conflict of interest can be sorted out by forwarding or delaying one of the two trains. If the first departure pattern is the most preferred option to operator one, then the latter departure is less profitable to her. In other words, there is a cost of forwarding or delaying the departure, a cost which is likely to be private information to each operator.

In terms of the notation used in section 2 these type I conflicts were characterised by $T_j = 3$ for all bidders. In other words, each operator had three alternative departures to place bids on. In addition, the three departures from x to y were identical for all operators that had redemption values for these departures in terms of departure and arrival time. This was also the case for the y to x departures.

During the first six experimental sessions subjects were confronted with this type of conflicts. Subjects faced between one and three such conflicts at a time in each one of the six sessions. During each of the six sessions, 2-4 individuals had redemption values over departures {*A, A, A*} and 2-4 over the departures {*B, B, B*} and therefore wanted to purchase an element from either of these. Graphically, this kind of conflict is represented by the first set of strings of the diagram in figure 1. Every operator always had a higher redemption value for the non-starred departure than for the starred departures.

Departures were sold under two constraints. First, only one out of the three alternatives in each package was sold. The intuition is that the three departures are so close to each other that no more than one could be sold at a time. Second, crossing strings, representing colliding trains, could not be sold.

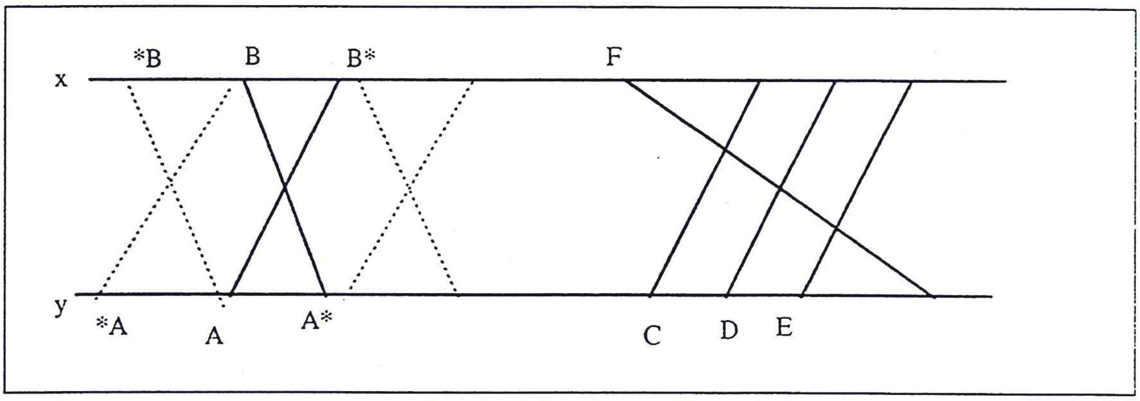

Figure 1: Stylised string diagram with 10 departures between adjacent stations x and y.

Type II conflicts. The second aspect that we want to capture in our testbed corresponds to the situation when there is a group of operators whose preferred use of the track is in conflict with a single operator. There is no conflict of interest between the operators within the group. Thus, the group members face a type of free rider problem. Hence, we conjecture that this situation might be problematic to the first but not to the second price auction(s) since the latter can be seen as a special case of a so called Clark-Groves mechanism (cf. Clarke 1971, Groves 1973, and Leonard 1983).

The type II conflicts were thus characterised by $T_j = 1$ for all operators, i.e. every subject was bidding on one single departure. Furthermore, there was only one departure from x (y) while there were three from y (x). The group of three were not in conflict with each other. This is the kind of conflict illustrated by the second set of strings in figure 1. Thus, 1-2 individuals had redemption values over each departure while no alternatives to each single path was considered. In total subjects were confronted with six sessions that included this type of conflicts. In two of these sessions subjects were presented with a single conflict and in the other four sessions they were presented with two conflicts of this type at a time.

Type III conflicts. This type of conflict is a more complex version of the type I conflict in that an additional string was drawn across the first set of strings in figure 1. The implication of this is that either one of the admissible solutions from the Type I conflicts above was sold, or that the extra string - say G - was sold to one of the subjects. These conflicts therefore both included aspects of conflict complexity and free riding incentives. From each of these four last sessions we have observations of one ‘super-complex’ conflict and in addition one ‘standard’ type I or type II conflict.

To summarise, subjects in the experiments were provided with redemption values over a number of departures. Each subject knew his/her own, but not the others' redemption values. The allocation problem with which they were presented differs from the traditional auctions of a single-item good in two respects. First, in some instances each good had an alternative and second, not all goods could be sold at the same time. In other words, the auctions were to decide which combination of goods that were to be sold and to whom.

4.2 Subjects, Training and Treatments

Each of eight groups of subjects have completed 15-16 buying sessions in our computerised experimental lab. A group included 6 - 8 undergraduate students from the economics and science classes at Dalarna University, none of which had any previous experience with economic experiments. Students were recruited with a promise to get at least 100 Swedish crowns (SKr) by participating in an experiment which would last at most two hours day 1 and at most four hours day 2. They were also informed that, in addition, they would earn according to performance during the experiments. The first two groups were pilot experiments and will not be reported in the present paper.

During day 1 the subjects participated in a series of training sessions. In all of these, pay-offs were hypothetical. Typically, simplified versions of the conflicts presented above were used. The last session of day 1 was a conflict of type I albeit with hypothetical pay-offs. Subjects were not informed about what they would be doing in the day 2 experiments.

During day 2 the final exercise from day 1 was repeated whereafter each group participated in 15-16 sessions where pay-offs were for real. The first six sessions were for type I conflicts, the next six for Type II and the last four for Type III conflicts. Each group bought departures using one of the pricing rules but both of the stopping rules. Redemption values were kept identical for all experiments, i.e. the values for, say, bidder number 6 were the same in each group. With respect to the differences in experimental treatments between groups it can be seen from Table 1 that groups 3, 4 and 7 bought departures in the second-price auctions and that groups 5, 6 and 8 in the first-price auctions.

Another treatment was that different patterns for the introduction of the different stopping rules were tested. From Table 1 we see that groups 3 and 5 started with ascending in the first three sessions, whereafter they were faced with one-shot bidding in the remaining three sessions on the type I conflicts. The other groups started with one-shot bidding. The bidding rules continued to switch between ascending and one-shot bidding in the type II and type III conflicts.

Column four of the table indicates a variation in the number of bidders between different groups. However, and as can be seen from the table, we also have a variation in the treatment concerning the order in which the stopping rule was introduced between these groups. To assess the (combined) effect of number of bidders and introduction of stopping rule on allocations we shall compare group 3 to 4 and group 5 to 6.

We presented the conflicts to groups 3-6 with an explicit context in the instructions while experiments 7 and 8 had no context. Context refers to that instructions provided complementary intuition by telling subjects that the items up for sale could be conceived of as the right to depart with a train from one place to another. (Translated instructions are available upon request.) The reason for using an explicit context was primarily that the ultimate aim is to run a large-scale experiment with subjects from the railway industry. Since it is not possible to use neutral instructions in that experiment, it seems less important to keep instructions neutral here. However, to keep some control of the effect of contextual instructions the two additional experiments without any context were also conducted.[2]

	Pricing principle	Ascending introduced first	Number of bidders	Type of instructions	Number of trading sessions	Bid grid
Group 3	Second	Yes	7 and 6[1]	Contextual	16	No
Group 4	Second	No	8	Contextual	16	No
Group 5	First	Yes	7 and 6[2]	Contextual	15	No
Group 6	First	No	8	Contextual	16	Yes
Group 7	Second	No	8	Neutral	16	No
Group 8	First	No	8	Neutral	16	Yes

Notes: (1) The number of bidders were initially 7 but after 3 trading sessions one bidder went bankrupt and had to leave the experiment thereby leaving us with 6 bidders for the remaining 13 trading sessions. (2) Compare with note 2; since we wanted to keep the number of bidders equal between the groups we "auctioned away" one of the subjects in group 3 after the third trading session to keep the number of bidders equal for each trading session in groups 1 and 3. By "auctioning away" we mean that we paid one subject in group 3 to leave the experiment where the price for leaving was determined by an English clock auction.

Table 1: Summary of the experimental treatments, groups 3-8.

The sixth column of the table simply shows how many buying sessions each group participated in. This number is equal for all groups but group 5 where session thirteen took an extremely long period of time. Hence, to keep the time-limit that we had set up for the entire experiment, session 3.2 was jumped. While this is not much of an experimental treatment, it is relevant information for the data analysis. This is also the reason why we introduced a "bid grid" for groups 6 and 8. The "bid grid" refers to the rule that bidders had to raise their bids by at least 10 SKr between different bidding rounds. The last column of the table indicates which groups that faced this rule and which groups that did not.

5. RESULTS

We will report about the results of the experiments under two headings, first which efficiency properties that can be observed (5.1) and secondly the relation between observed bidding behaviour by individuals as compared to predicted behaviour (5.2).

5.1 Efficiency

Final allocations are evaluated by means of the traditional performance or efficiency measure (E^1) used in experimental economics, namely

---

[2] We thank Glenn W. Harrison for making this suggestion.

$E^1 = (S^r/S^{max})*100$

S^r is the surplus observed in the experiment(s) and S^{max} the maximum possible surplus (cf. Davis & Holt (1993) p. 132). Thus, E^1 measures how large fraction of the maximum possible surplus that is realised in a specific allocation.

In table 2 we find the averages of E^1 for each group and stopping rule. Here we do not distinguish between different types of conflicts. The allocations are obviously on average very good, efficiencies ranging between 97.7% and 100%. This gives us our first result.

Result 1: Average efficiencies are high in all auctions.

	One-shot	Ascending
Group 3 - Second Price	98.8 (2.28)	97.9 (4.69)
Group 4 - Second Price	98.8 (2.87)	97.7 (3.58)
Group 5 - First Price	98.4 (2.20)	99.8 (0.53)
Group 6 - First Price	99.0 (2.02)	100.0 (0)
Group 7 - Second Price	99.8 (0.91)	99.1 (2.24)
Group 8 - First Price	98.5 (2.34)	99.4 (1.34)

Table 2. Average Efficiencies over eight one-shot and eight ascending bidding sessions separated by auction type. Standard deviation in parenthesis.

In order to assess whether the results of groups 3, 4 and 7 and those of groups 5, 6 and 8, respectively, are significantly different from each other we employ a Kruskal-Wallis test. This serves two purposes. First, are the results sensitive to the variation in treatments between the groups (see table 1)? Second, if they are not, we can pool the results for the different groups.

In neither of the second price auctions test results indicate significant differences between the realised efficiencies. Likewise, the test results for groups 5, 6 and 8 suggest that there is no significant difference between the efficiencies realised in the first price one-shot auction. However, there is a difference at the 10 percent significance level between the three groups realised in the first price ascending auction. A Wilcoxon two sample test reveals that this is due to a significant difference at the 5 percent level between the realised efficiencies of groups 6 and 8. This indicates that the use of neutral instructions in the first price ascending auction leads to lower efficiencies than when we use instructions that provide a context for the goods being sold.

Result 2a: There are no indications of learning effects from whether the one-shot or the ascending stopping rule is introduced first or that a (small) variation of the number of bidders make a difference.
Result 2b: There are only weak indications of that the use of context in instructions makes a difference for the outcome of the experiment.

It is thus possible to combine results for groups 3, 4 and 7 that bought departures in the second price auctions for each of the stopping rules. Also the results of first price auctions in groups 5, 6 and 8 can be pooled, but only for the one-shot while not for the ascending auction. This gives us table 3.

When testing whether there are any differences between the four auctions a pair-wise Wilcoxon two sample test reveals the following. (i) The first price ascending auction produces significantly better allocations than the other auctions at the 1 percent level of significance. This is true when using the pooled results of groups 5 and 6. However, when also the results of group 8 are used there are no significant differences between the first price ascending auction and the other three auctions. (ii) The second price auction produce significantly better allocations than the first price one shot and the second price ascending auctions at a significance level of 10 percent. However, there is no significant difference between the second price ascending and the first price one-shot auctions at the 10 percent level of significance.

To summarise these observations, we first ignore the results obtained with group 8 (first price ascending auction). Second, we accept the significance level of 10 percent as sufficient to provide indication of differences between auctions. Using $\succ$ to denote that the auction to the left of the sign leads to better allocations than that to the right of the sign, and $\sim$ to indicate that there are no efficiency differences, we get the following ranking of the auctions in terms of realised efficiencies, stated as result 3.

Result 3: First Price Ascending $\succ$ Second Price One-shot $\succ$ First Price One-shot $\sim$ Second Price Ascending

	No. of groups/sessions per group/conflicts per group	Efficiency
Groups 3, 4 and 7 - Second Price Ascending	3/8/15	98.2 (3.62)
Groups 3, 4 and 7 - Second Price One-shot	3/8/15	99.2 (2.17)
Groups 5 and 6 - First Price Ascending	2/7 and 8, respectively/ 13 and 15, respectively	99.9 (0.36)
Group 8 First Price Ascending	1/8/15	99.4 (1.34)
Groups 5, 6 and 8 - First Price One-shot	3/8/15	98.6 (2.15)

Table 3. Average Efficiencies of Pooled Results. Standard deviation in parenthesis.

Let us now turn to the realised efficiencies in the different types of conflicts that were used and see if there are any differences between the auctions. The results from a series of Wilcoxon two-sample tests (not reported here) indicate that results from groups 3, 4 and 7, and from groups 5, 6 and 8 can be pooled except in one case. Thus, in table 4 we present the average efficiencies in the groups for which we could pool the results for each type of conflict.

Conflicts of Type I	One-shot	Ascending
Group 3+4 - Second Price	97.6 (3.34)	95.4 (5.30)
Group 7 - Second Price	100 (0)	98.7 (3.22)
Group 5+6+8 - First Price	98.8 (1.99)	99.8 (0.58)
Conflicts of Type II		
Group 3+4+7 - Second Price	99.9 (0.82)	99.6 (1.14)
Group 5+6+8 - First Price	98.7 (2.56)	99.7 (1.08)
Conflicts of Type III		
Group 3+4+7 - Second Price	100 (0)	99.2 (1.23)
Group 5+6+8 - First Price	98.1 (1.54)	99.6 (0.92)

Table 4. Average Efficiencies by Group, Stopping Rule and Type of Conflict. Standard deviations in parenthesis

Using a Wilcoxon 2-sample test, pair-wise comparisons have been made between the different groups in order to identify significant differences. The outcome of these tests are reported in terms of the ranking found as result 4 (ignoring group 7).

Result 4a: Conflict type I - First Price Ascending ≻ Second Price One-shot, Second Price Ascending and First Price One-shot;
First Price One-shot ≻ Second Price Ascending;
First Price One-shot ~ Second Price One-shot;
Second Price One-shot ~ Second Price Ascending

Result 4a: Conflict type II - First Price Ascending ≻ First Price One-shot ;
First Price Ascending ~ Second Price One-shot and Second Price Ascending;
Second Price One-shot ≻ First Price One-shot;
Second Price One-shot ~ Second Price Ascending;
Second Price Ascending ~ First Price One-shot;

There are only two observations on the conflict of type III for each group and stopping rule, and these results have not been systematically compared to the others.However, the results in table 4 for this type of conflicts indicate that the auctions have per performed very well also in these conflicts.

5.2 Bidding Behaviour[3]

To see whether the high efficiencies reported in section 5.1 are due to bidders behaving according to some economically sensible bidding strategies we now turn to analyse the bidding behaviour in each of the four auctions. We begin with the second price and the first price one-shot auctions before turning to the ascending auctions.

[3]Here we report data on the bidding behaviour in the one-shot auctions. Data on the bidding behaviour in the ascending auctions will be available at the conference.

In table 5a we present the relative difference between the bids and the values for the different departures in the second price one-shot auction. Obviously, individuals both overbid and nderbid in this auction. We also see that in groups 3 and 4 bidders do not seem to follow the predicted strategy of bidding the true valuations. At least not on the starred departures since here the bids are more below the value than on the non-starred alternatives. While only five sessions out of 18 had an average bidding behaviour with bids deviating more than 5% from value on the A/B option, 18 out of 36 averages deviate with more than 5% from the value on the *A/*B and A*/B* departures.

However, note also how close the bids in group 7 are to the true values of the departures - both for the starred and the non-starred departures. Thus, the bidding behaviour in group 7 is close to the predicted behaviour. Furthermore, this behaviour explains the high efficiencies reached by group 7 in the second price one-shot auction in the conflicts of type I (see table 4).

Table 5b contains the corresponding information about the type II conflicts. Here, we see no average deviation exceeding the (arbitrarily chosen) 5% limit. In addition, standard deviations are low. The second price one-shot auction obviously generates an actual behaviour closer to predictions when confronted with this class of conflicts. We can not say if this can be explained by that incentives in type I conflicts are more difficult to grasp than in type II conflicts, or if a learning aspect is involved. However, we can say that the high efficiencies observed for the second price one-shot auction reported in table 4 in the conflicts of type II are due to that bidders behave quite close to the predicted bidding behaviour.

		1	2	3	4	5	6
	***A/*B**	-0.18 (0.40)	-0.34 (0.52)	-0.19 (0.40)	-0.40 (0.49)	-0.36 (0.50)	-0.47 (0.52)
3	**A/B**	-0.02 (0.04)	-0.18 (0.40)	-0.02 (0.05)	0.00 (0.02)	0.00 (0.01)	-0.16 (0.34)
	A*/B*	-0.18 (0.40)	-0.18 (0.40)	-0.19 (0.40)	-0.34 (0.52)	-0.46 (0.51)	-0.47 (0.52)
	***A/*B**	0.01 (0.04)	-0.08 (0.70)	-0.12 (0.36)	-0.11 (0.36)	0.01 (0.03)	0.01 (0.02)
4	**A/B**	0.02 (0.07)	-0.09 (0.67)	-0.11 (0.36)	-0.10 (0.36)	0.02 (0.03)	0.01 (0.03)
	A*/B*	0.02 (0.04)	-0.08 (0.70)	-0.24 (0.47)	-0.12 (0.36)	0.02 (0.03)	0.01 (0.03)
	***A/*B**	0.01 (0.01)	0.01 (0.02)	0.00 (0.02)	0.01 (0.01)	0.00 (0.01)	0.02 (0.03)
7	**A/B**	0.01 (0.02)	0.01 (0.02)	0.02 (0.03)	0.01 (0.01)	0.01 (0.02)	0.01 (0.02)
	A*/B*	0.01 (0.01)	0.01 (0.02)	0.00 (0.01)	0.01 (0.02)	0.00 (0.02)	0.02 (0.02)

Table 5a. Mean of Quotient (Bid-Value)/Value in the One-Shot Second Price Auction. Type I conflicts. Standard deviation in parenthesis.

	1	2	3	4	5	6
3	-0.002 (0.020)	0.002 (0.006)	0.002 (0.006)	0.010 (0.013)	0.003 (0.006)	0.017 (0.035)
4	0.017 (0.035)	0.017 (0.025)	0.024 (0.043)	0.028 (0.037)	0.034 (0.045)	0.016 (0.044)
7	0.024 (0.052)	0.008 (0.048)	-0.100 (0.047)	0.086 (0.146)	0.029 (0.033)	-0.030 (0.174)

Table 5b. Mean of Quotient (Bid-Value)/Value in the One-Shot Second Price Auction. Type II conflicts. Standard deviation in parenthesis.

We do not have any clear behavioural predictions when it comes to the **one-shot first price auction**. It is, however, obvious that bids above redemption value can never generate a surplus for the bidder. We observe no such bids in the conflicts of type I. Hence, the efficiencies realised in the conflicts of type I for this auction is not due to some random behaviour.

Table 6 provides information on the bidding behaviour in the type II conflicts where there existed some free rider incentives. Referring back to Figure 1, we mean by 'team' the group of 6 individuals that had values over trains C, D and E. In contrast, 'non-team' bidders are the two subjects bidding for F. Obviously, it is among the 'team' bidders that we would expect free riding. Making pair-wise comparisons of 'teams' and 'non-teams' it is equally obvious that, with one exception, 'teams' place (much) lower bids than 'non-teams'. Thus, there seem to exist some free riding among the bidders in the team. This might explain the relatively poor performance of the first price one-shot auction when applied to the conflicts of type II.

Team bidders					
	241	251	252	261	262
5	-0.25 (0.103)	-0.23 (0.031)	-0.14 (0.061)	-0.15 (0.034)	-0.14 (0.082)
6	-0.12 (0.065)	-0.08 (0.033)	-0.07 (0.021)	-0.10 (0.040)	-0.10 (0.056)
8	-0.16 (0.027)	-0.11 (0.052)	-0.12 (0.028)	-0.12 (0.055)	-0.11 (0.085)
Non team bidders					
5	-0.06 (0.044)	-0.08 (0.058)	-0.09 (0.037)	-0.13 (0.089)	-0.05 (.)
6	-0.08 (0.023)	-0.08 (0.039)	-0.08 (0.032)	-0.05 (0.005)	-0.03 (0.014)
8	-0.04 (0.005)	-0.06 (0.043)	-0.03 (0.007)	-0.07 (0.046)	-0.07 (0.015)

Note: (.) implies that there were only one bidder on this departure.

Table 5b Mean of (Bid-Value)/Value in the One-shot First Price Auction, conflicts of Type II. Standard deviation in parenthesis.

6. CONCLUDING DISCUSSION

The results presented in this paper shows that it is premature to dismiss the idea of using some kind of auction to allocate the right to use railway track capacity among different train operators. This conclusion is based on the high efficiencies of the realised allocations and that these allocations were reached for the right reason - bidding behaviour in each auction seem in general to be consistent with what we expected for each respective auction. Thus, there is good reason to subject the mechanisms to more severe challenges by adding complexity to the testbed environments and continue the process of trying to find a suitable auction for allocating the right to use railway track capacity.

It is difficult to present a decisive ranking of the auctions in terms of their relative performance in producing good allocations since all auctions perform well in the experiments. The bidding behaviour in the first price ascending auction seems to lead to the most efficient allocations, irrespective of the type of situation in which we test the auctions. However, we are still not certain about the performance of this auction in situations with stronger free riding incentives than those used in the series of experiments presented in this paper. In these situations the bidding behaviour in the second price auctions might lead to better allocations since observed behaviour in these auctions was very close to the behaviour that leads to the efficient allocations.

Furthermore, we found one potential problem with the first price one-shot auction which might be difficult to solve. This is the free riding behaviour observed in the situations where there was a team of bidders against a non-team of bidders (the conflicts of type II) which was the explanation to the relatively low efficiencies realised in this auction applied to this specific type of situation.

Finally, when there existed an earlier or later alternative to the most preferred departure (the conflicts of type II) the bidding behaviour in the second price auctions resulted in relatively low efficiencies for the conflicts of type I. However, this is perhaps more of learning problem related to the relatively sophisticated pricing principle used in these auctions than a serious shortcoming of the auctions.

References

BANKS, J.S., J.O. LEDYARD, D.P. PORTER (1989). Allocating Uncertain and Unresponsive Resources: An Experimental Approach. *RAND Journal of Economics*. **Vol. 20**, No. 1.

BREWER, P.J., C. R. PLOTT (1996). A Binary Ascending Price (BICAP) Mechanism for the Decentralized Allocation of the Right to Use Railroad Tracks. *International Journal of Industrial Organization*, **Vol. 14**.

CLARKE, E.H. (1971). Multipart Pricing of Public Goods. *Public Choice* **Vol. 11**, (Fall) pp. 17-33.

DAVIS, D. D., C. A. HOLT (1993). *Experimental Economics*. Princeton University Press.

DEMANGE, G, D. GALE, M. SOTOMAYOR (1986). Multi-Item Auctions. *Journal of Political Economy*. **Vol. 94** (no. 4), pp 863-872.

GROVES, T. (1973). Incentives in Teams. *Econometrica*, **Vol. 41** (July), pp. 617-631.

KOOPMANS, T. C., M. BECKMANN (1957). Assignment Problems and the Location of Economic Activities. *Econometrica*, **Vol. 25**.

LEONARD, H.B. (1983). Elicitation of Honest Preferences for the Assignment of Individuals to Positions. *Journal of Political Economy*, **Vol. 91**, (No. 3).

McAFFEE, R.P., J. McMILLAN (1996). Analyzing the Airwaves Auction. *The Journal of Economic Perspectives*, **Vol. 10** (No. 1).

McCABE, K.A, S.J. RASSENTI, V.L. SMITH (1989). Designing 'Smart' Computer-Assisted Markets: An Experimental Auction for Gas Networks. *Journal of Political Economy*, **Vol. 5**.

NILSSON, J.-E. (1995). Swedish Railways Case Study. In Kopicki, R. and L.S. Thomson (eds.). *Best Methods of Railway Restructuring and Privatization*. CFS Discussion Paper No. 113, World Bank.

--- (1996). Allocation of Track Capacity. Experimental Evidence on the use of Priority Auctioning in the Railway Industry. *Working Paper*, CTS, Dalarna University.

OLSON, M., D. PORTER (1994). An Experimental Examination into the Design of Decentralized Methods to Solve the Assignment Problem With and Without Money. *Economic Theory*, **Vol. 4** (No. 1), pp 11-40.

PLOTT, C.R. (1994). Designer Markets: Laboratory Experimental Methods in Economics. *Economic Theory*, **Vol. 4** (No. 1), pp 3-10.

RASSENTI, S.J., SMITH, V.L., R.L. BULFIN (1982). A Combinatorial Auction Mechanism for Airport Time Slot Allocation. *Bell Journal of Economics*, **Vol. 13**, pp. 402-417.