Behavior in All-Pay and Winner-Pay Auctions with Identity-Dependent Externalities*

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Abstract

In many economic environments players are not indifferent to the outcome of a contest given that it is not their most preferred one. If a player's valuation depends on the identity of the outcome/winner of the contest rather than just the state of winning or losing, this player is said to experience identity-dependent externalities.

In this article we experimentally investigate all-pay and winner-pay auctions with positive and negative identity-dependent externalities. We use a symmetric three player environment with complete information. The results of the experiment indicate that behavior strongly depends on the payoff space. Although the all-pay auction yields higher revenue than the winner-pay auction in environments with negative identity-dependent externalities (caused by both overbidding in the all-pay and under-bidding in the winner-pay auction), average revenue and bids approximate their theoretical predictions closely in treatments with positive identity-dependent externalities or without identity-dependent externalities when subjects are experienced. Furthermore, we observe in the all-pay auction treatments that even experienced subjects do not randomize continuously but rather follow bimodal strategies.We estimate coefficients for risk- and loss-aversion and find that the observed bid distributions are well explained when allowing for an s-shaped utility function.

JEL C72, C91, D44, D62, D72
Keywords: all-pay auction, winner-pay auctions, externalities, laboratory experiments.

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1 Introduction

The idea that a player's payoff depends on the allocation of the prize in the event that she does not win the prize herself has recently attracted much interest within the theoretical literature on auctions. Equilibrium behavior in most standard winner-pay auction formats with identity-dependent externalities (short IDE) has been analyzed[1]. Jehiel and Moldovanu (2006) provide an excellent summary of specific phenomena that arise in winner-pay auctions due to identity-dependent externalities. Klose and Kovenock (2011) analyze the all-pay auction with complete information and IDE. IDE trigger many new phenomena regarding equilibrium behavior and payoffs even in environments with complete information.

However, most of the analysis of auctions with IDE is yet theoretically. Although some experiments of winner-pay auctions with IDE and incomplete information occur in the literature, to the best of our knowledge, we are the first to experimentally investigate all-pay and winner-pay auctions with IDE and complete information[2].

Our experiment is built on a simple environment in which three identical players with complete information compete for a single prize in an all-pay or winner-pay auction. It differs from existing all-pay and winner-pay auction experiments in that we introduce positive and negative IDE, i.e. a player's valuation of losing is not always zero but depends on the identity of the winner. In particular, with positive IDE, one of the two losers still has a positive valuation of losing in the case that her counterpart wins the auction. Similarly, with negative IDE, one of the two losers has a negative valuation of losing if her counterpart wins the auction. The results of our experiment indicate that IDE play a significant role when one compares revenue of the all-pay and winner-pay auction in a given environment.

[1]See for example Das Varma (2002) or Funk(1996).

[2]Linster et al. (2001) investigate a Tullock-type contest with identity-dependent externalities and complete information, they find on average lower bids than the theoretical predictions. Bagchi and Shur (2006), Hu, Kagel and Ye (2009) and Kirchkamp and Moldovanu (2004) analyze laboratory experiments of winner-pay auctions with identity-dependent externalities and incomplete information.

We find that the sign of IDE, and hence on the payoff space, affect bidding behavior in both auction formats differently. Although we observe that in both auction formats revenues qualitatively change in the right direction when IDE are introduced, the magnitude of revenue changes differs across auction formats and with the sign of IDE. In particular, we observe that the revenue in both the all-pay and winner-pay auctions with positive IDE is lower than without IDE, and it is higher with negative IDE than without IDE. However, the magnitude of the change differs strongly across treatments. On the one hand, when subjects are experienced (in the second half of a session) revenue in both all-pay and winner-pay treatments with positive IDE do not differ significantly from each other as well as from the theoretical prediction. On the other hand, subjects increase their bid by too much/little in the all-pay/winner-pay treatment in response to the introduction of a negative IDE of the same magnitude. This results in a significant spread between revenues of the all-pay and winner-pay treatments with negative IDE even in the last observed periods.

Our investigation of behavior in the treatments with externalities further helps us to understand bidding in auctions without IDE. In particular, most experimental studies of the all-pay auction document aggregate overdissipation, i.e. the sum of bids exceeds the value of the prize far more often than expected.[3]. Davis and Reilly(1998) argue that such overbidding is not caused by risk preferences, an explanation often used to explain overdissipation in winner-pay auctions. Gneezy and Smorodinsky (2006) argue that neither fully rational nor boundedly rational models of players' behavior can explain the pattern of overdissipation in all-pay auctions. Another possible explanation that can be found in the literature is that overdissipation is caused by a non-monetary utility of winning (See Goeree et al., 2002; Sheremeta, 2010). However, given that bidding behavior strongly varies across our treatments with and without IDE, from no aggregate overdissipation in the all-pay auction

[3]Baye et al. (1999) investigate overdissipation in rent-seeking contests. Gneezy and Smorodinsky(2006) and Lugovskyy et al. (2010) find empirical evidence for substantial overdissipation in all-pay auction experiments with complete information.

with positive IDE to extreme overbidding in the all-pay auction with negative externalities, we conclude that the non-monetary utility of winning is not the main driving force behind overbidding in all-pay auctions. Yet another explanation for overdissipation in all-pay auctions comes from Lugovskyy et al.(2010). They conjecture that part of the overdissipation (on the aggregate and individual level) is caused by bidders who perceive bidding zero as being inactive which in turn biases them to submit strictly positive bids. They further test this conjecture in a treatment that uses a transformed bidding space[4] and find that, although aggregate overdissipation appears to be very robust in their experiment, this transformation in conjunction with extensive repetition and a partners protocol eliminates overdissipation. In contrast, our experiment uses a strangers matching protocol and the time horizon is half shorter. In such an environment we find substantial amounts of zero bids throughout all treatments, and there is no overbidding relative to the risk-neutral Nash equilibrium prediction in the all-pay auction treatment with positive IDE. On the other hand, in treatments with negative IDE the magnitude of overbidding is even higher than in the all-pay auction without IDE. This strongly suggests that the finding of Lugovskyy et al. (2010) is not caused by the removal of a bias towards active participation, but rather by transforming the payoff space from the negative to the positive.

Additionally, we observe that subjects use mixed strategies in all three all-pay auction treatments, randomizing is however not continuous as predicted but rather bimodal. Subjects rarely submit intermediate bids, but predominantly choose very low or high bids. This phenomenon has previously been observed in experimental studies of the all-pay auction with complete information and no IDE (see for example Potters et al.,1998). Ernst and Thöni (2010) find that bimodal bidding in an all-pay auction can be explained by loss aversion and estimate parameters of a utility function that is consistent with prospect theory to fit their

[4] In their baseline subjects are asked to submit non-negative bids for a prize of value 1000, in the treatment with the transformed bidding space they submit bids greater or equal to -1000 for a prize of value zero.

data. We do the same for our treatments with and without IDE and find support for the hypothesis that bidding behavior in all-pay auctions is influenced by loss-aversion.[5]

In the winner-pay auction treatments we observe in early periods that subjects underbid in comparison to the predicted pure strategy equilibrium. In the treatment with negative IDE this underbidding persists even when subjects are experienced. Here average bids remain significantly lower than predicted across all periods. Furthermore, subjects' bids are distributed over a wider range than expected from a pure strategy equilibrium. We find that our observations are in line with the findings of early experiments on simple Bertrand competition (e.g. Dufwenberg and Gneezy, 2000).

In the environment that we employ in our experiment theory predicts revenue equivalence of the all-pay and winner-pay auctions, however, based on the bidding behavior described before, we find that revenue equivalence breaks down in the laboratory. The results of our experiment show that the all-pay auction generates significantly higher revenue than the winner-pay auction in treatments with negative IDE. Although the same difference is initially observed in other treatments, it finally disappears after subjects have gained sufficient experience. Such a ranking of the two auction formats is consistent with previous experimental findings on auctions with incomplete information. For instance, Noussair and Silver (2006) find a similar revenue ranking for a single-unit all-pay auction with independent private values.[6].

The rest of the paper is organized as follows. Section 2 outlines the theory behind the auction mechanisms used in our experiment. The experimental design and procedures are described in Section 3. Section 4 presents experimental finding and section 5 provides some

[5]Ert and Erev (2010) claim that the pattern predicted by loss aversion emerges only under very specific conditions.

[6]Barut et al. (2002) show that independent-value all-pay and winner-pay auctions are empirically revenue equivalent when multiple units are sold. Eisenhuth(2010) shows for environments with incomplete information that revenue in the all-pay auction is higher than in the first-price winner-pay auction when players are loss averse.

interpretation. Finally, Section 6 concludes.

2 Theoretical Model

We consider all-pay and winner-pay acutions with positive and negative identity-dependent externalities. We use a symmetric three player environment with complete information. Each player may have a preference over who receives the prize in the event that it is not her. We denote player i's valuation for player j winning the auction as v_{ij}, where $i, j \in \{1, 2, 3\}$. In this notation, v_{ii} corresponds to player i's own valuation of winning the prize. A general valuation matrix is shown in Figure 1a. We further assume that players are symmetric and have the following valuations as in Figure 1b: $v_{11} = v_{22} = v_{33} = v, v_{12} = v_{23} = v_{31} = \alpha$, and $v_{13} = v_{21} = v_{32} = 0$, where $v > 0$ and $\alpha < v$ varies according to the treatment.

(a)

$$\begin{pmatrix} v_{11} & v_{12} & v_{13} \\ v_{21} & v_{22} & v_{23} \\ v_{31} & v_{32} & v_{33} \end{pmatrix}$$

(b)

$$\begin{pmatrix} v & \alpha & 0 \\ 0 & v & \alpha \\ \alpha & 0 & v \end{pmatrix}$$

Figure 1: Valuation Matrices ($v > 0$, $v > \alpha$)

In each auction, each player $i, i \in \{1, 2, 3\}$, simultaneously chooses a bid x_i. The player with the highest bid wins the auction. In order to keep all players symmetric, we assume that ties are broken randomly.[7] The crucial difference between all-pay and winner-pay auctions is that in the all-pay auction, all three players forgo their bids, while in the winner-pay auction, only the winner forgoes her bid. In the winner-pay auction, the expected payoff of a representative player 1 is equal to player 1's probability of winning the prize, p_1, times her prize valuation ($v_{11} = v$) minus the cost of her chosen effort, x_1, plus player 2's probability

[7] Funk (1996), in a setting of a winner-pay auction with identity-dependent externalities, considers the limiting case similar to the common practice for first-price winner-pay auctions without IDE.

of winning, p_2, times $v_{12} = \alpha$:[8]

$$E\pi^{WP}(x_1, x_2, x_3) = p_1(v - x_1) + p_2 \cdot \alpha. \tag{1}$$

Under our assumptions there exists a unique symmetric pure strategy Nash equilibrium of the winner-pay auction. In a symmetric pure strategy equilibrium all three players must submit identical bids. The following strategy profile is the only one that satisfies all conditions to be a symmetric pure strategy Nash equilibrium:

$$x_1^* = x_2^* = x_3^* = v - \frac{1}{2}\alpha. \tag{2}$$

Player i's, $i \in \{1, 2, 3\}$, expected payoff in this equilibrium is

$$E\pi^{WP}(x^*) = \frac{1}{3}\left[v - \left(v - \frac{1}{2}\alpha\right)\right] + \frac{1}{3}\alpha = \frac{1}{2}\alpha.$$

It is easy to show that player i cannot improve her payoff with any higher or lower bid, given that both opponents bid $v - \frac{1}{2}\alpha$. On the other hand, assume that all players bid $b < v - \frac{1}{2}\alpha$, then player i's, $i \in \{1, 2, 3\}$, payoff is $\frac{1}{3}(v - b) + \frac{1}{3}\alpha$ and she can improve her payoff by increasing her bid to $b + \epsilon$, $\epsilon \in \left(0, \frac{2}{3}(v - b) - \frac{1}{3}\alpha\right)$. Assume that all players bid $b > v - \frac{1}{2}\alpha$, then a player could improve by decreasing her bid to $b - \epsilon, \epsilon > 0$. Therefore, the equilibrium described above is unique within the class of symmetric pure strategy equilibria[9].

In the all-pay auction, the expected payoff of a representative player 1 is equal to player 1's probability of winning the prize p_1 times her prize valuation, $v_{11} = v$, plus player 2's

[8]Note that $v_{13} = 0$ by assumption.

[9]When $\alpha = 0$ there exists a continuum of asymmetric equilibria, in which two players tie at x^* and the third player submits any lower bid. When $\alpha \neq 0$ these equilibria do not exist and the equilibrium described in (2) is unique.

probability of winning, p_2, times $v_{12} = \alpha$, minus the cost of her chosen effort x_1:

$$E\pi^{AP}(x_1, F(x_2), F(x_3)) = p_1 \cdot v + p_2 \cdot \alpha - x_1. \tag{3}$$

Similar to a standard all-pay auction without externalities (Baye et al., 1996), there are no pure-strategy Nash equilibria in this environment. However, there exists a unique symmetric mixed-strategy Nash equilibrium. Let F^* represent the cumulative distribution function, according to which all players randomize their bids. It is necessary that the support of F^* is continuous and starts at zero. Otherwise there would be an interval in which players submit a bid with probability zero. In that case a player could improve her payoff by moving mass from the upper limit of the interval to the lower limit. Given these properties, we can write a player's expected payoff from a bid, x, in the support of F^* as

$$E\pi^{AP}(x, F^*, F^*) = (F^*(x))^2 \cdot v + F^*(x)[1 - F^*(x)](\alpha + 0) + [1 - F^*(x)]^2 \cdot \frac{\alpha + 0}{2} - x$$

The unique cumulative distribution function F^* that maximizes $E\pi^{AP}$ is:

$$F^*(x) = \begin{cases} 0 & x < 0 \\ \left(\frac{x}{v - \frac{1}{2}\alpha}\right)^{\frac{1}{2}} & 0 \leq x \leq v - \frac{1}{2}\alpha \\ 1 & x > v - \frac{1}{2}\alpha \end{cases} \tag{4}$$

Player i's expected payoff in this equilibrium is $E\pi^{AP}(F^*) = \frac{1}{2}\alpha$ and her expected bid is $\frac{1}{3}\left(v - \frac{1}{2}\alpha\right)$. For our predictions of the behavior of subjects in the experiment, we focus solely on these symmetric equilibria[10]. Note that the expected payoff in the all-pay auction is the same as in the winner-pay auction for these equilibria, i.e. $E\pi^{WP*} = E\pi^{AP*} = \frac{1}{2}\alpha$.

[10]We randomly and anonymously rematch subjects every period, therefore it is unlikely that players would be able to coordinate and play an asymmetric equilibrium.

3 Experimental Design, Predictions and Procedures

3.1 Experimental Design and Predictions

The design of our experiment consists of six treatments as shown in Table 1. The two base line treatments AP and WP correspond to simple first-price all-pay (AP) and winner-pay (WP) auctions with symmetric players and no IDE. Although the nature of the equilibrium in the all-pay auction is different from the winner-pay auction, the two mechanisms are theoretically revenue equivalent in the chosen environments. The two treatments AP-P and WP-P correspond to the all-pay (AP) and winner-pay (WP) auctions with positive (P) IDE, $\alpha = 60$. The final two treatments AP-N and WP-N correspond to all-pay and winner-pay auctions with negative (N) IDE, $\alpha = -60$. The theoretical prediction is again that the all-pay auction is revenue equivalent to the respective winner-pay auction, i.e. that WP-P is revenue equivalent to AP-P, and WP-N is revenue equivalent to AP-N.

Table 1: Experimental Design and Theoretical Predictions

Treatment	Values v, α	Average Bid	Expected Payoff	Expected Revenue R
AP	100, 0	33.3	0	100
WP	100, 0	100	0	100
AP-P	100, 60	23.3	30	70
WP-P	100, 60	70	30	70
AP-N	100, -60	43.3	-30	130
WP-N	100, -60	130	-30	130

Another theoretical prediction is that with positive IDE, $\alpha > 0$, the revenue collected in both auction formats is lower than in the respective auction without IDE. The basic intuition behind this result is that with positive externalities the expected payoff of losing in the symmetric equilibrium is positive causing players to bid less aggressively and not all the way up to their valuation of winning the prize. Similarly, with negative IDE, $\alpha < 0$, the expected payoff of losing is always negative which encourages bidders to bid more than their initial valuation of the prize.

Hypothesis 1. *Avarage revenues in the environments under consideration are ranked as follows:* $R_{AP-P} = R_{WP-P} < R_{AP} = R_{WP} < R_{AP-N} = R_{WP-N}$.

From section 2 we also derive the following hypotheses regarding equilibrium bidding behavior and payoffs.

Hypothesis 2. *In winner-pay auction treatments subjects choose the pure strategy* $v - \frac{1}{2}\alpha$.

Hypothesis 3. *In all-pay auction treatments subjects randomize according to the mixed strategy (4), with the average bid of* $\frac{1}{3}\left(v - \frac{1}{2}\alpha\right)$.

3.2 Experimental Procedures

A total of 144 subjects participated in twelve sessions (12 subjects per session). All subjects were undergraduate students who participated in only one session of this study. Some students had participated in other economics experiments that were unrelated to this research. The computerized experimental sessions were run using z-Tree (Fischbacher, 2007). Throughout the session no communication between subjects was permitted and all choices and information were transmitted via computer terminals.

Upon arrival, subjects were given the instructions, available in the Appendix, and the experimenter read the instructions aloud. Before the actual experiment, subjects completed a quiz to verify their understanding of the instructions. Each session corresponded to 30 periods of play in one of the treatments. In each period, subjects were randomly and anonymously placed into 4 groups with 3 participants in each group. At the beginning of the first period, subjects were randomly assigned a role either as participant 1, 2 or 3. Subjects maintained the same role assignment for the entire session. Each consecutive period subjects were randomly re-paired with two other participants of opposite assignments to form a new three-person group. Each period subjects placed their bids (no more than 150 francs) and after all subjects had submitted their bids, the computer chose the participant with the highest bid as the winner. The valuations of each subject in each treatment were assigned as in Table 1. In the winner-pay auction treatments (WP, WP-P and WP-N) only the winners had to forfeit their bids, while in the all-pay auction treatments (AP, AP-P and AP-N) all participants had to forfeit their bids. At the end of each period the computer displayed all bids made by each participant in the same group, the participant who received the reward and individual earnings for the period.[11]

At the end of the experiment, 3 out of 30 periods were randomly selected for payment. The earnings were exchanged at a rate of 25 francs = \$1. Additionally, all subjects received an initial endowment of \$15 to cover potential losses.[12] On average, subjects earned \$20 each, which was paid anonymously and in cash. The experimental sessions lasted for about 70 minutes.

4 Results

4.1 Revenue Comparison

Table 2 summarizes by treatment the average bid, payoff and revenue for the last 15 periods and for all 30 periods of the experiment. The first notable feature of the data is that the average revenue collected in the all-pay auctions is higher than the average revenue collected in the winner-pay auctions by the magnitude of 20%-80%. The random-effect models, with revenue as the dependent variable and treatment as the independent variable,

[11] At the end of the session subjects also participated in a short surprise experiment, which is not included in this study.

[12] Subjects were also given additional \$5 at the end of all sessions with no externalities and \$10 at the end of all sessions with negative externalities. These additional payments were made to ensure that subjects have received a substantial amount of money at the end of the experiment.

indicate that the revenue differences are significant (p-values < 0.01)[13]. It is important to

Table 2: Average Bid, Payoff and Revenue in All Treatments

	Bid			Payoff			Revenue		
		Average			Average			Average	
	Predicted	16-30	1-30	Predicted	16-30	1-30	Predicted	16-30	1-30
AP	33.3	37.7	45.1	0	-4.3	-11.8	100	113	135.3
WP	100	87.7	80.2	0	0.78	1.8	100	97.7	94.5
AP-P	23.3	21.1	23.9	30	32.3	29.4	70	63.2	71.7
WP-P	70	50.5	47.4	30	32.6	33.7	70	62.2	59.0
AP-N	43.3	59.8	65.1	-30	-46.5	-51.7	130	179.5	195.2
WP-N	130	96.0	93.2	-30	-22.6	-21.7	130	107.9	105.9

emphasize, however, that there is substantial learning that takes place in the experiment. Figure 2 displays the average revenue over all periods of the experiment. There is a significant declining revenue trend in all all-pay auction treatments, especially in the first half of each session. On the other hand, the average revenue in the winner-pay treatments slightly increases over periods[14]. As a result, in periods 16-30, the revenues of the all-pay and winner-pay auction do not differ significantly in treatments without IDE and with positive IDEs.

Result 1a When subjects do not have sufficient experience, the all-pay auction generates higher revenue than the winner-pay auction in all treatments.

[13]To support this conclusion we estimate three panel regressions for the positive, negative and no externalities. In each regression the dependent variable is revenue and independent variable is a treatment dummy-variable (all-pay versus winner-pay). Each model includes a random effects error structure, with the individual subject as the random effect, to account for the multiple decisions made by individual subjects. The standard errors are clustered at the session level. Based on the estimation, treatment dummies are significant in all three specifications (p-values < 0.01), indicating that the revenue in the all-pay auction is higher than the revenue in the winner-pay auction.

[14]A simple regression of the revenue on a period trend shows a significant and negative relationship in AP-N and AP treatments (p-value < 0) but not in the AP-P treatment (p-value $= 0.22$). On the other hand, there is a significant and positive relationship in WP-N and WP treatments (p-value < 0.01) but not in WP-P (p-value $= 0.30$).

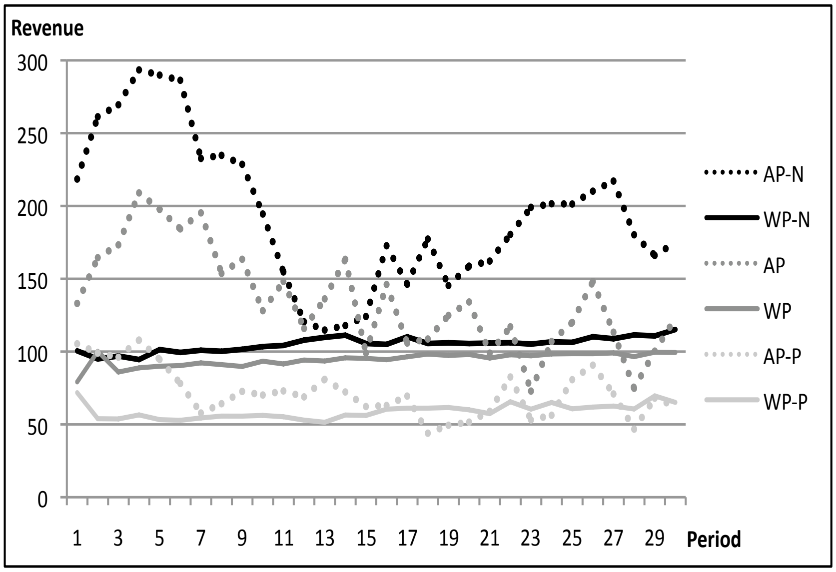

Figure 2: Average Revenue over Periods

Result 1b When subjects are experienced, the all-pay auction generates higher revenue than the winner-pay auction only in an environment with negative IDE.

The actual magnitude of the revenue collected in the all-pay auction is significantly higher than the theoretically predicted values for the AP-N and AP treatments (p-values are 0.01 and 0.06), but not for the AP-P treatment (p-value = 69). The difference between predicted and realized revenue is most extreme in the AP-N treatment. Here theory predicts revenue of 130, while the average collected revenue throughout the experiment is 195.2, a difference of roughly 50 percent. This difference is significant even when we look at only the last 15 periods of the experiment. The difference between predicted and realized revenue is not statistically significant in the AP and AP-P treatments when looking at the last 15 periods of the experiment.

Result 2 The revenue collected in the all-pay auction with negative IDE is statistically significantly higher than predicted. There is no significant difference between predicted and realized revenue in the all-pay auction without and with positive IDE.

The picture is very different when looking at the winner-pay auction. Here, the revenues collected in the WP, WP-P, and WP-N treatments (94.5, 59.0, and 105.9) are lower than the theoretical predictions (100, 70, and 130). The difference is significant when looking at all periods of the experiment, as well as when looking at the last 15 periods of the experiment (p-values < 0.01).

Result 3 The revenue collected in all winner-pay auctions (without, with negative, and with positive IDE) is significantly lower than predicted.

The data clearly supports our theoretical revenue ranking as stated in Hypothesis 1. The revenue collected decreases from 135.3 in AP to 71.7 in AP-P and it decreases from 94.5 in WP to 59.0 in WP-P. The revenue collected increases from 135.3 in AP to 195.2 in AP-N and it increases from 94.5 in WP to 105.9 in WP-N. The differences are significant based on the estimation of random effect models (all p-values < 0.01).[15]

Result 4 As predicted, the revenue collected in both the all-pay and the winner-pay auctions without IDE is lower than with negative IDE, and it is higher than with positive IDE in the respective auction format.

4.2 Bidding Behavior

4.2.1 Winner-Pay Auction Treatments

Convergence of Average Bids In all three winner-pay auction treatments, contrary to Hypothesis 2, we observe that average bids are lower than their theoretical prediction (see Figure 3). We do, however, observe that average bids are slowly increasing over time. The estimation of an asymptotic convergence model as in Noussair et al. (1995) shows that

[15]To support these conclusions we estimate panel regressions. In each regression the dependent variable is revenue and independent variable is a treatment dummy-variable (positive and negative externality). Each model includes a random effects error structure, with the individual subject as the random effect, to account for the multiple decisions made by individual subjects. The standard errors are clustered at the session level. Based on the estimation, treatment dummies are significant in all specifications (p-values < 0.01).

average bids do not converge to the predicted level of 130 in the WP-N, 100 in the WP, and 70 in the WP-P treatment.[16]

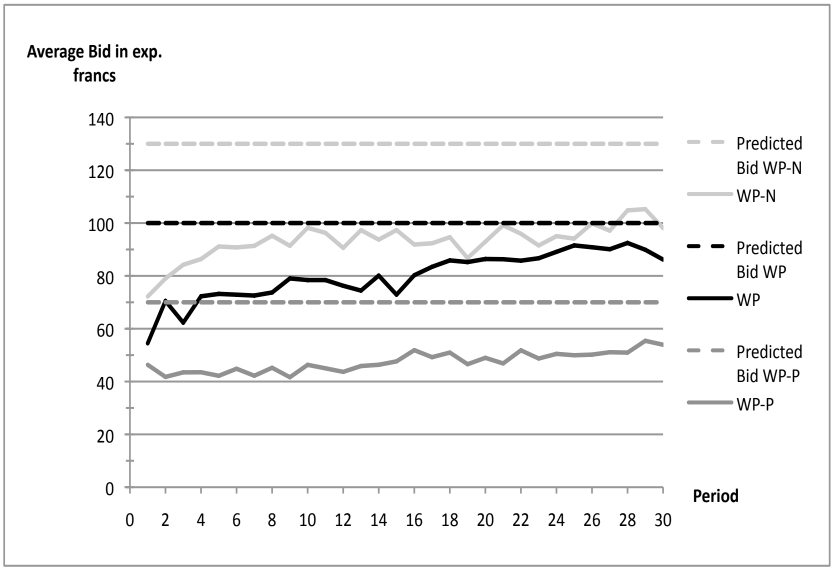

Figure 3: Average bids over time in winner-pay auction treatments

Result 5 Average bids increase over time in all winner-pay auctions. However, even with experienced subjects, average bids remain lower than predicted.

Our observations are comparable to those known from simple Bertrand competition experiments, e.g. Dufwenberg and Gneezy(2000). In these experiments, subjects typically submit prices that are higher than the equilibrium prediction resulting in positive profits. Similarly, in the winner-pay auction with complete information subjects submit bids lower than the value of the prize, and thus they on average receive positive profit.

Bid Distribution Next we look at the distribution of bids in the winner-pay auction (Figure 4). In all three treatments the distribution of bids follows similar pattern. For

[16] In each regression the dependent variable is bid and independent variables are constant and a subject-specific inverse of a period trend. The standard errors are clustered at the session level. Based on the estimation, the asymptotic constant variable is significantly different from theoretical predictions (p-value = 0.06 in WP-N, p-value = 0.05 in WP, and p-value = 0.09 in WP-P).

example, in the WP treatment about 5% of bids are greater than 100 (the equilibrium prediction). Bids are distributed on the entire strategy space between 0 and 150, with the majority of bids skewed to the left of the theoretical distribution. As subjects receive more experience (the last 15 periods of the experiment), more high bids and fewer low bids are submitted and the empirical distribution shifts to the right. This provides some evidence of learning towards equilibrium predictions. Similar patterns are observed in the winner-pay auctions with IDE. In the WP-P treatment about 5% of bids are greater than theoretically predicted 70 and in the WP-N treatment only about 1% of bids are greater than predicted 130. Again, bids are distributed on the entire strategy space. As learning takes place, both distributions shift to the right.

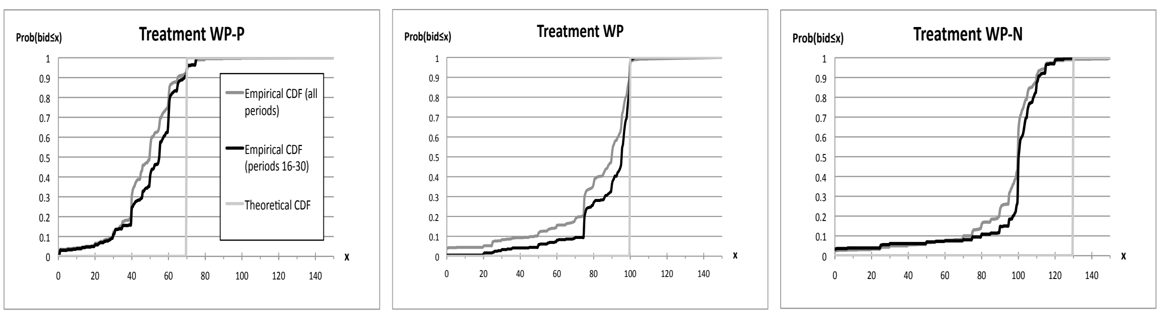

Figure 4: Bid distribution in Winner-Pay Auction Treatments

Distribution of Winning Bids The distribution of winning bids in the winner-pay auction treatment without externalities (WP) resembles the theoretical prediction very closely. More than 80% of winning bids are between 90 and 110. The winning bids for the remaining two treatments (WP-P and WP-N) are spread over a slightly larger interval. Only 40% of the winning bids are between 60 and 80 in the WP-P treatment, and 5% of the winning bids are between 120 and 140 in the WP-N treatment. These observations are clearly reflected in our observations regarding average revenues, given that the winning bids constitute the revenue in a first-price winner-pay auction.

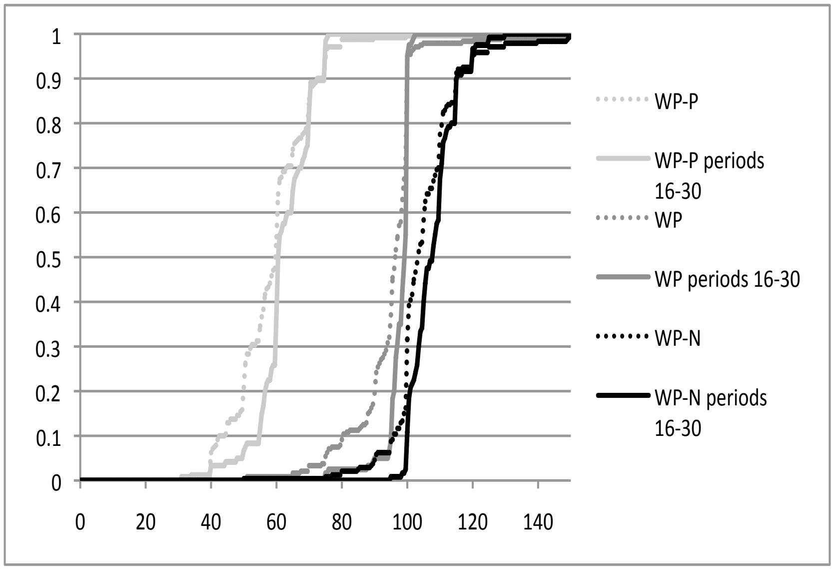

Figure 5: Distribution of Winning Bids in Winner-Pay Auction Treatments

4.2.2 Observations in All-Pay Auction Treatments

Convergence of Average Bids In comparison to the winner-pay auction treatments, we observe more variation of the average bid in all three all-pay auction treatments. This is not surprising, however, given that the equilibrium is in mixed strategies. Also, in contrast to the winner-pay auction treatments and contrary to Hypothesis 3, there is an aggregate over-bidding in all all-pay auction treatments. Average bids slowly decrease over time, indicating learning. According to the estimation of an asymptotic convergence model the average bid converges to the average predicted level of 33.3 in the AP treatment (p-value = 0.49) and 23.3 in the AP-P treatment (p-value = 0.63), but it does not converge to 43.3 in the AP-N treatment (p-value = 0.07).

Result 6 Average bids decrease over time in all all-pay auctions. With sufficient experience, average bids in the all-pay auction without and with positive IDE converge to the predicted levels. However, average bids in the all-pay auction with negative IDE are always higher than predicted.

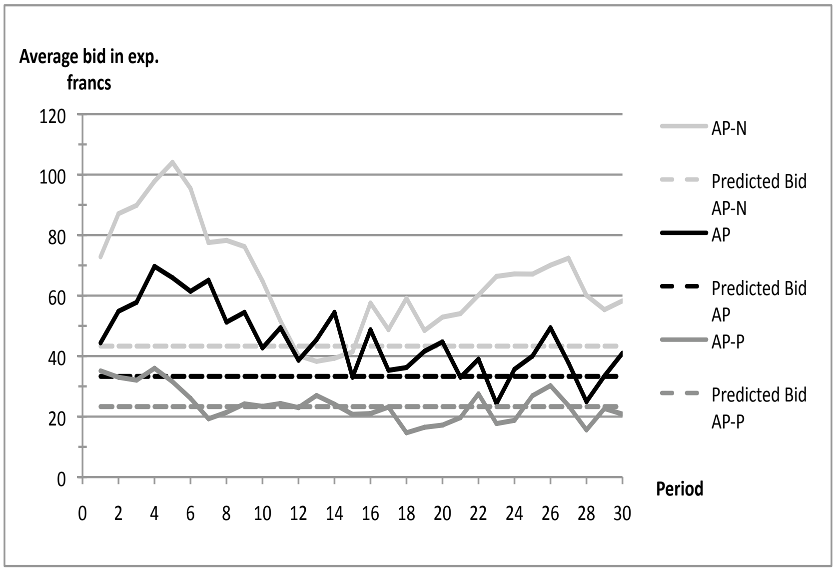

Figure 6: Average Bids over time in all-pay auction treatments

Similar to previous experiments on all-pay auctions (e.g. Gneezy and Smorodinsky(2006)), we observe aggregate overbidding which decreases with experience. In our experiment, the overbidding is most pronounced in the all-pay auction with negative IDE (AP-N treatment). The qualitative difference is also visible when we compare the empirical distribution of bids to the theoretically predicted cumulative distribution function for each of our three all-pay auction treatments.

Bid Distribution Figure 7 illustrates the bid distributions in all-pay auction treatments. Analyzing the distribution of bids, one can see that, although average bids in the AP and AP-P treatments converge towards the predicted level, the distribution functions do not. The dichotomous nature of bidding behavior does not disappear with experience (the last 15 periods of the experiment).

Overall, we observe qualitatively the same bid distribution function, showing two 'jumps', in all three all-pay auction treatments. Figure 7 illustrates that, in the AP treatment, almost 40% of all bids are below 10 (bottom tail of the distribution) and 20% are above 90 (upper tail of the distribution), leaving only 40% of bids between 10 and 90. Similarly, in the AP-P (AP-N) treatment about 40% (30%) of all bids are in the bottom and about 25% (30%) are in the upper tail of the distribution. It is important to emphasize that such dichotomous nature of bidding behavior is consistent with experimental studies of Barut et al. (2002) and Ernst and Thöni (2010).

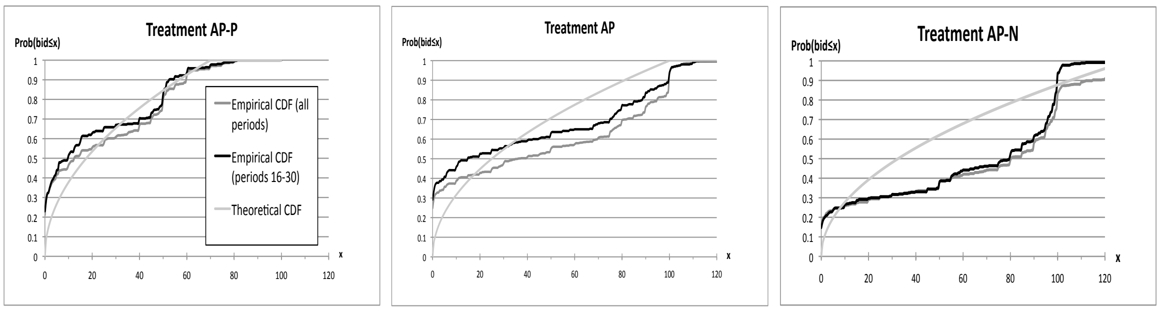

Figure 7: Bid Distribution in All-Pay Auction Treatments

5 Possible Explanations

5.1 Winner-Pay Auction Treatments

As mentioned earlier, our findings in the winner-pay auction treatments are very much in line with those known from simple Bertrand experiments and therefore little surprising. In each winner-pay auction treatment we observe some rent-seeking. In the WP treatment (Figure 4), most subjects submit bids lower than 100 with much mass concentrated around 75, hoping to earn some positive payoff rather than the equilibrium payoff zero. Similarly, in the WP-P treatment, we observe excessive bidding around 60 and 40 rather than the equilibrium bid 70. While the bid of 60 appears to be the equivalent of the bid of 75 in the WP treatment, we observe another masspoint at 40. Note that winning with a bid of 40 yields the same payoff as losing at zero and benefitting from the externality, i.e. 100-40=60.

Therefore, a winner who wants to earn as much as the "lucky" loser, needs to win at 40. In the WP-N treatment, the mass is centered around 100. Again, winning with a bid of 100 yields the same payoff as being the "lucky" loser and receiving 0, i.e. 100-0=0. Thus, both mass points in winner-pay auctions with IDE can be explained by a simple behavioral model.

Finally, there are some subjects who submit bids higher than predicted and others who submit very small bids. Bids above the predicted equilibrium bid can be explained by risk aversion. Moreover, some subjects seem to mix their bids, although there is a simple symmetric pure strategy equilibrium.

5.2 All-Pay Auction Treatments

The data indicate that most subjects in all-pay auction treatments vary their bids over time, however, they do not place bids everywhere within the theoretical support, but rather mix between some high value and some low value, with few subjects hardly mixing at all (see Figures 13 -15 in the appendix). In contrast to Lugovskyy's et al. (2010) conjecture of a bias towards active participation, we find a substantial number of very low bids in the all-pay auction treatment without IDE, AP. Low bids are particularly attractive to subjects who prefer avoiding losses. While the probability of winning is very small for low bids, subjects who submit low bids limit their losses to a very small number or completely eliminate the chance of losses by bidding zero. On the other hand, if subjects submit large enough bids, then they compete very aggressively choosing only bids close to the upper end of the support. In this range a subject who strongly tries to avoid any losses will submit a higher bid, which increases her chance of winning, but decreases her profit in the case she wins.

In the all-pay auction treatment with positive IDE, AP-P, both strategies become more attractive due to the fact that even a loser may not make a loss if she experienced a positive externality. We observed that most winning bids are less than 60 francs, these bids have the characteristic that they do not necessarily result in a loss if the subject loses. In our AP-N treatment the argument works in the opposite direction. Given that most winning bids do not exceed the value of the prize significantly, a subject who aims to avoid losses will try and submit a bid that is high enough to win.

Next we try to quantify the predictive power of a model that incorporates loss aversion. We do so by estimating a utility function to fit our data.

5.2.1 Loss Aversion

Many of our earlier findings suggest that loss aversion may explain the particular bimodal bid distribution in the all-pay auction treatments. To formally test this hypothesis, similarly to Ernst and Thöni(2009), we assume that the players' (identical) utility function takes the form

$$u(x) = \begin{cases} x^{\eta} & x \geq 0 \\ -\lambda(-x)^{\eta} & x < 0 \end{cases} \tag{5}$$

and then estimate the parameters η and λ assuming that subjects bid according to the cumulative distribution function

$$F^{*}(x) = \left(\frac{\frac{1}{2}\left(u(\alpha) - u(-x) - u(\alpha - x)\right)}{u(v-x) - \frac{1}{2}\left(u(\alpha - x) + u(-x)\right)} \right)^{\frac{1}{2}}, \quad 0 \leq x \leq 150. \tag{6}$$

Given that our subjects are randomly drawn from the same subject pool, we first use a pooled regression assuming that the underlying utility function is identical for all subjects across all treatments. However, based on the very different exposure to losses across the treatments and in line with Ert and Erev's (2010) findings we allow the loss aversion parameter, λ, to vary across treatments in a second semi-pooled regression. Table 3 presents the coefficients that minimize the squared errors and 90% confidence intervals determined by bootstrapping. Similarly, Figure 8 displays the utility functions that result from the estimation.

Table 3: Utility Function Estimates

coefficient	Pooled	AP-P	AP	AP-N
η	0.4007	0.4719	0.4719	0.4719
90% CI	[0.3878, 0.4143]	[0.4588, 0.4849]	[0.4588, 0.4849]	[0.4588, 0.4849]
λ	0.5895	1.0381	0.6705	0.3310
90% CI	[0.5750, 0.6057]	[0.9979, 1.0852]	[0.6608, 0.6808]	[0.3227, 0.3398]

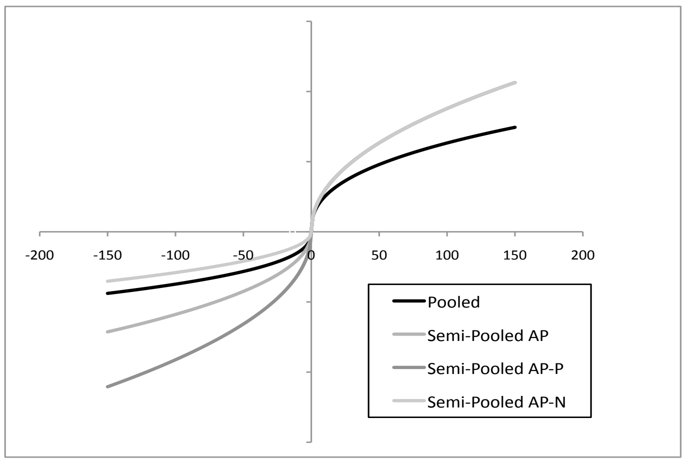

Figure 8: S-Shaped Utility Functions Fitted to All-Pay Auction Treatment Data

First, notice that the parameter η is for both regressions in the range between 0 and 1, showing that an S-shaped utility function fits our data the best, i.e. subjects are risk averse over gains and risk seeking over losses. Under the specified utility function (5), the coefficient of relative risk aversion is constant and equal to $(1 - \eta)$. Our parameter estimate is in the range of relative risk aversion parameters that can be found in the literature.

The parameter λ represents the degree of loss aversion. Similar to Ernst and Thöni (2009) we find an estimate that is strictly smaller than one in our pooled regression. When we allow loss aversion to be sensitive to the treatment, we still find parameters that are smaller than 1 in the treatment without IDE and with negative IDE. This suggests that subjects in these treatments react more sensitive to gains than they are to losses. Ernst and Thöni (2009) suggest that this kind of risk tolerance may be triggered by the extremely competitive nature of the contest. The fact that our estimate of λ is smaller for the more competitive treatment AP-N supports this conjecture. On the other hand, in the less competitive environment AP-P, in which bids are more likely to result in gains, we estimate a parameter that is greater than one. Note that our estimates for the more competitive environments AP and AP-N also differ significantly from the estimates that can be found in the literature, e.g. Kahneman and Tversky(1992) report $\lambda = 2.25$ and Booij et al. (2007) report $\lambda = 1.58$. Our estimates, however, are based on decisions made in a competitive environment and not on choices over lotteries.

Figure 9 shows the improved fit of the theoretical and empirical cumulative distribution of bids, when we allow for an S-shaped utility function. Although the estimated utility functions predict bimodal bidding in all three environments (with positive, negative, and without IDE) the fit in the environment with positive IDE is not as good as in the other two environments. This might be caused by the fact that losses do not arise as often in the environment with positive IDE.

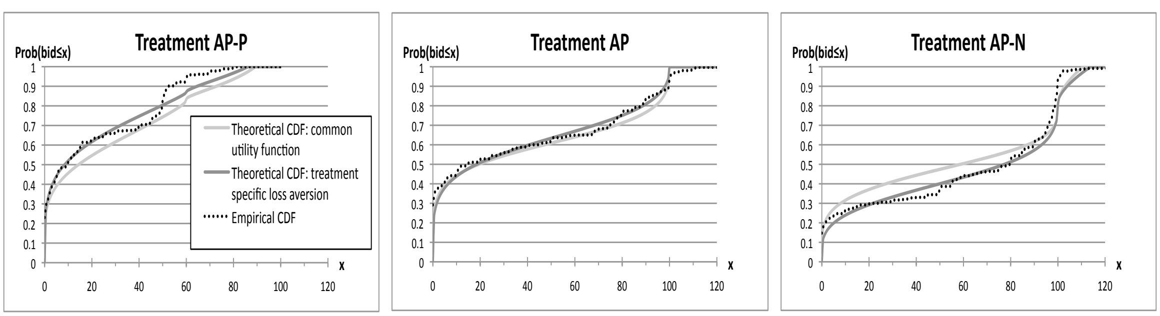

Figure 9: Comparison of Empirical CDF to Estimated CDF that Allows for Risk Preferences and Loss Aversion

6 Conclusions

We experimentally investigated all-pay and winner-pay auctions in a simple environment with three identical players and complete information. As a novel approach, we introduced positive and negative identity-dependent externalities. The results of the experiment indicate that in all treatments the all-pay auction initially yields higher revenue than the winner-pay auction. However, with experienced subjects, the revenue equivalence breaks down only for auctions with negative externalities. As predicted, the revenue in the all-pay and winner-pay auctions without eternities is higher than with positive IDE, and it is lower than with negative IDE. Although the positive and negative IDE which we introduce are of the same magnitude, the effects on average bids and thus revenue are not. The decrease of average bids, that we observe when comparing treatments with positive IDE to treatments without IDE, is stronger than the increase of average bids, that we observe when comparing treatments with negative IDE to treatments without IDE.

We further analyzed bidding behavior and found differences between the empirical and theoretical bid distributions for most treatments, even when average bids were close to theoretical predictions. Most specifics of the bidding distributions in the winner-pay auction treatments are in line with findings from earlier experiments on simple Bertrand competition. In the all-pay auction treatments we observe that while most individuals appear to use mixed strategies, they do not distribute their bids continuously. We used a simple model of an s-shaped utility function to explain the observed bid distribution and estimated parameters of risk aversion and loss aversion based on the observed bids. Our estimates suggest that subjects do not exert strong loss aversion in highly competitive environments in which competition often results in losses. On the other hand, in a less competitive environment with positive externalities our estimated parameter is in the range of parameters that were obtained in the literature.

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Appendix

Instructions Treatment AP-N[17]

GENERAL INSTRUCTIONS

This is an experiment in the economics of strategic decision making. Various research agencies have provided funds for this research. The instructions are simple. If you follow them closely and make appropriate decisions, you can earn an appreciable amount of money.

During this experiment you will be confronted with a decision problem that requires you to make a series of economic choices which determine your total earnings. The currency used in this experiment is francs. Francs will be converted to U.S. Dollars at a rate of 25 francs to 1 dollar. You have already received a $15.00 participation fee. At the end of today's experiment, you will be paid in private and in cash. There are 12 participants in today's experiment.

It is very important that you remain silent and do not look at other people's work. If you have any questions, or need assistance of any kind, please raise your hand and an experimenter will come to you. If you talk, laugh, exclaim out loud, etc., you will be asked to leave and you will not be paid. We expect and appreciate your cooperation.

At this time we proceed to a detailed description of the experiment.

[17]Instructions for the remaining treatments are very similar and available upon request.

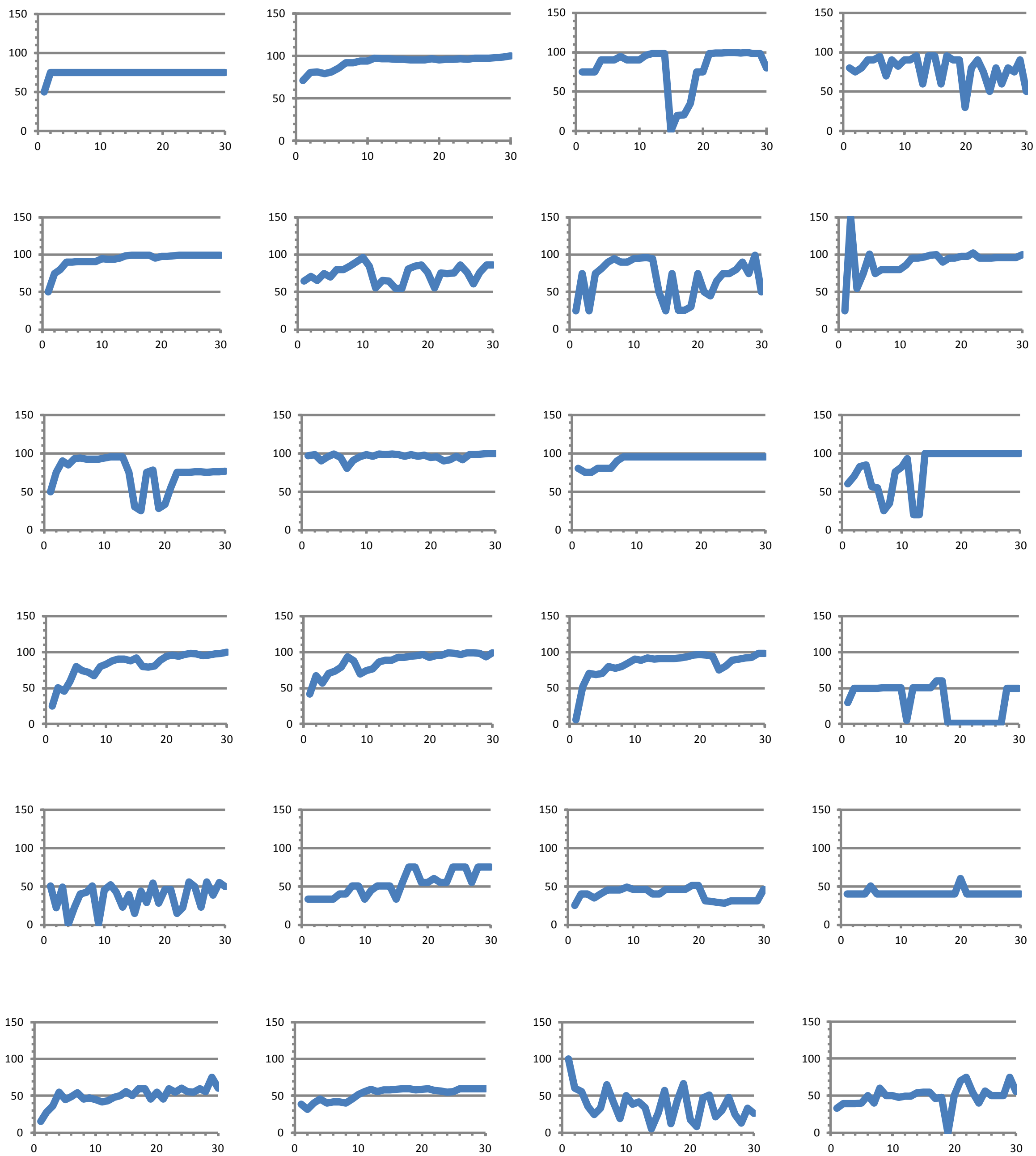


Figure 10: Individual bids in WP-P treatment

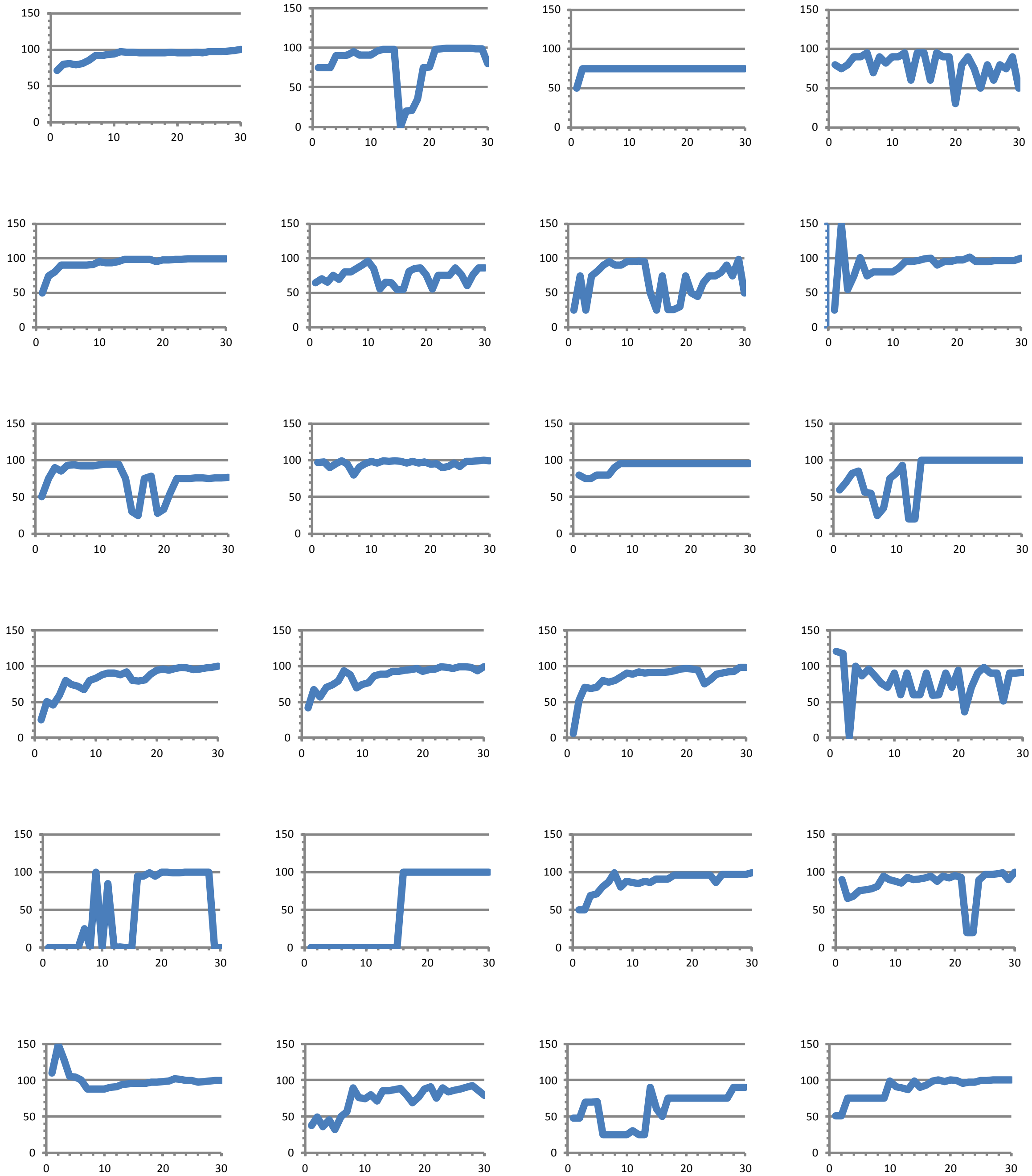


Figure 11: Individual bids in WP treatment

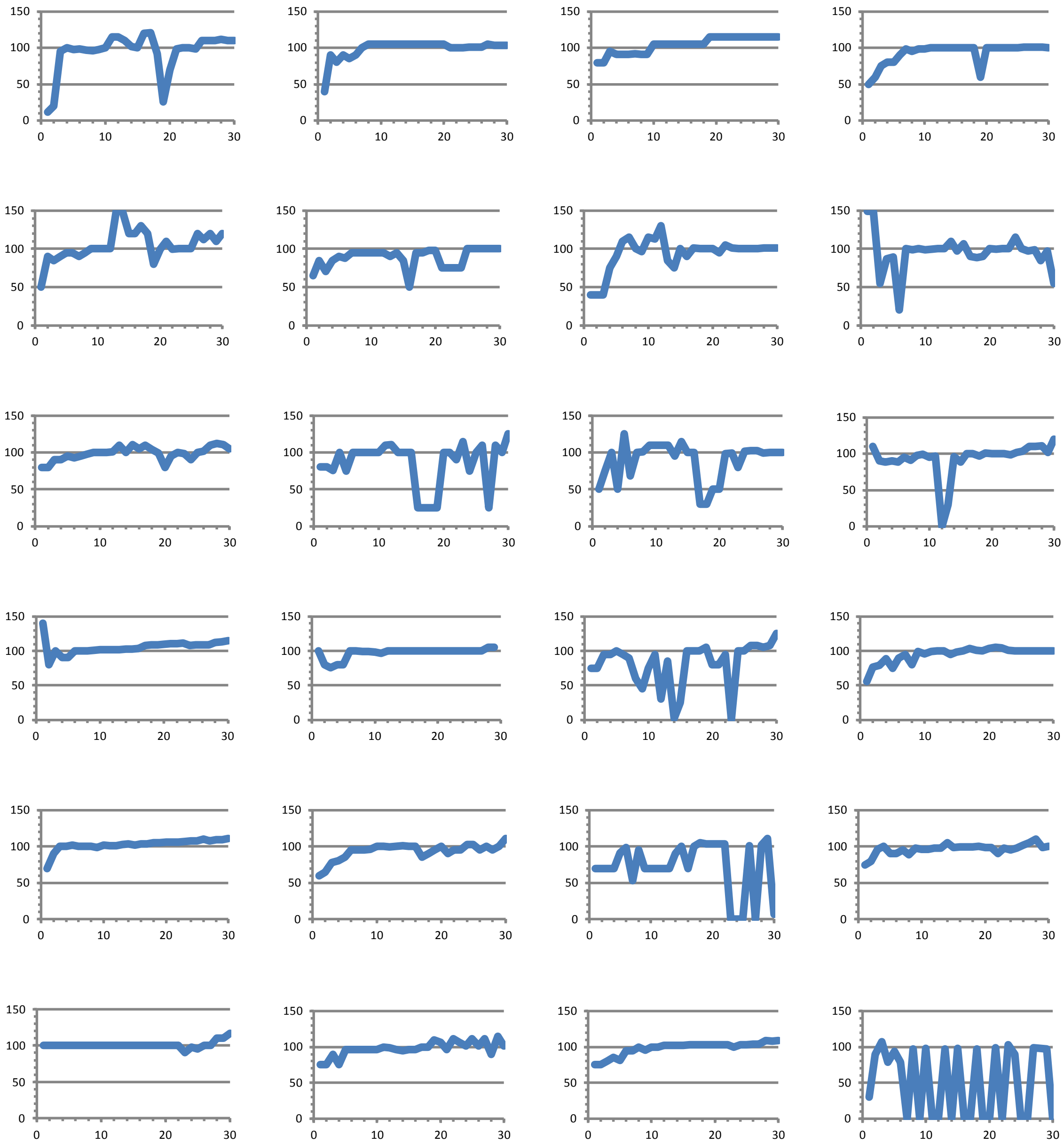


Figure 12: Individual bids in WP-N treatment

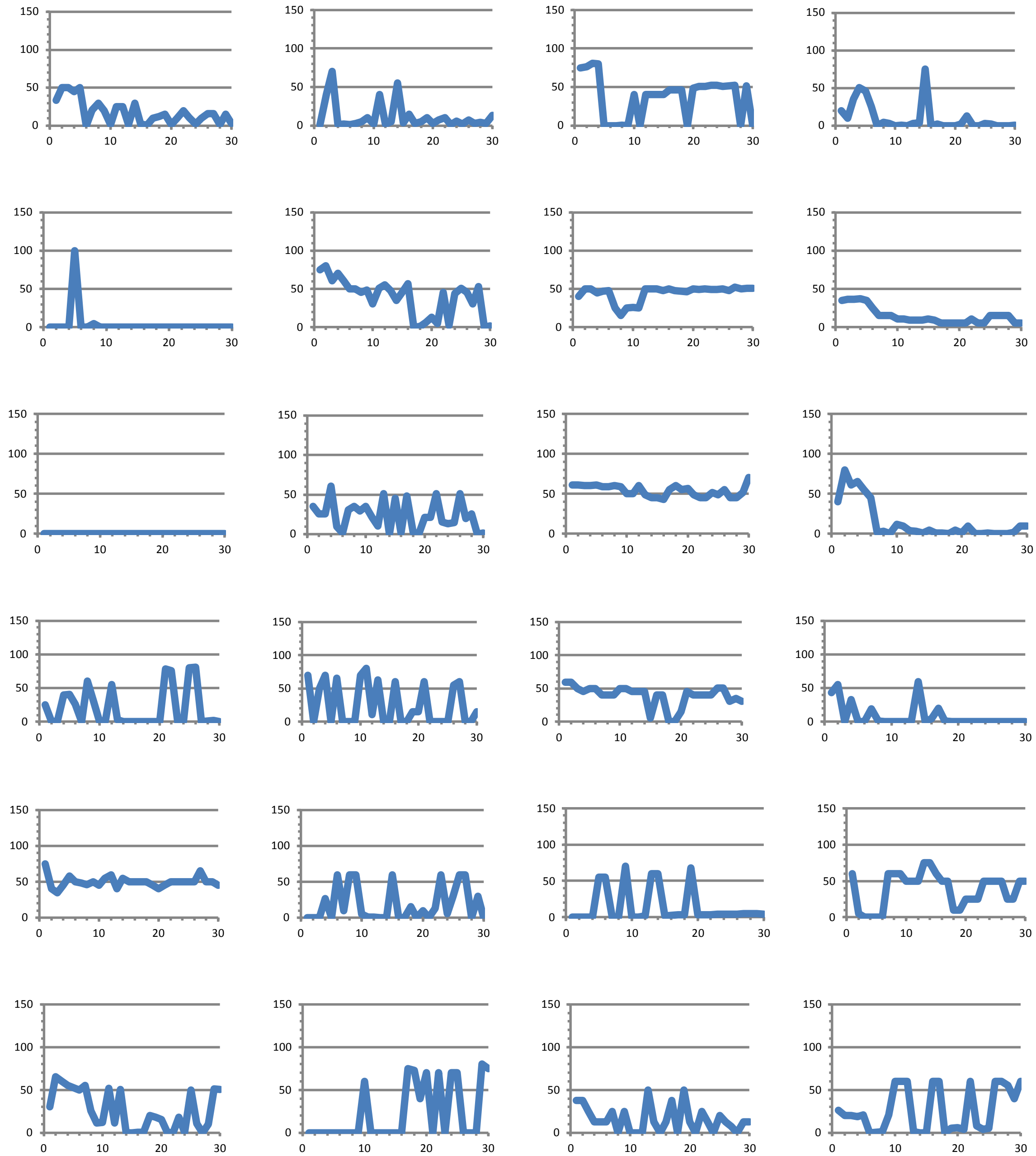


Figure 13: Individual bids in AP-P treatment

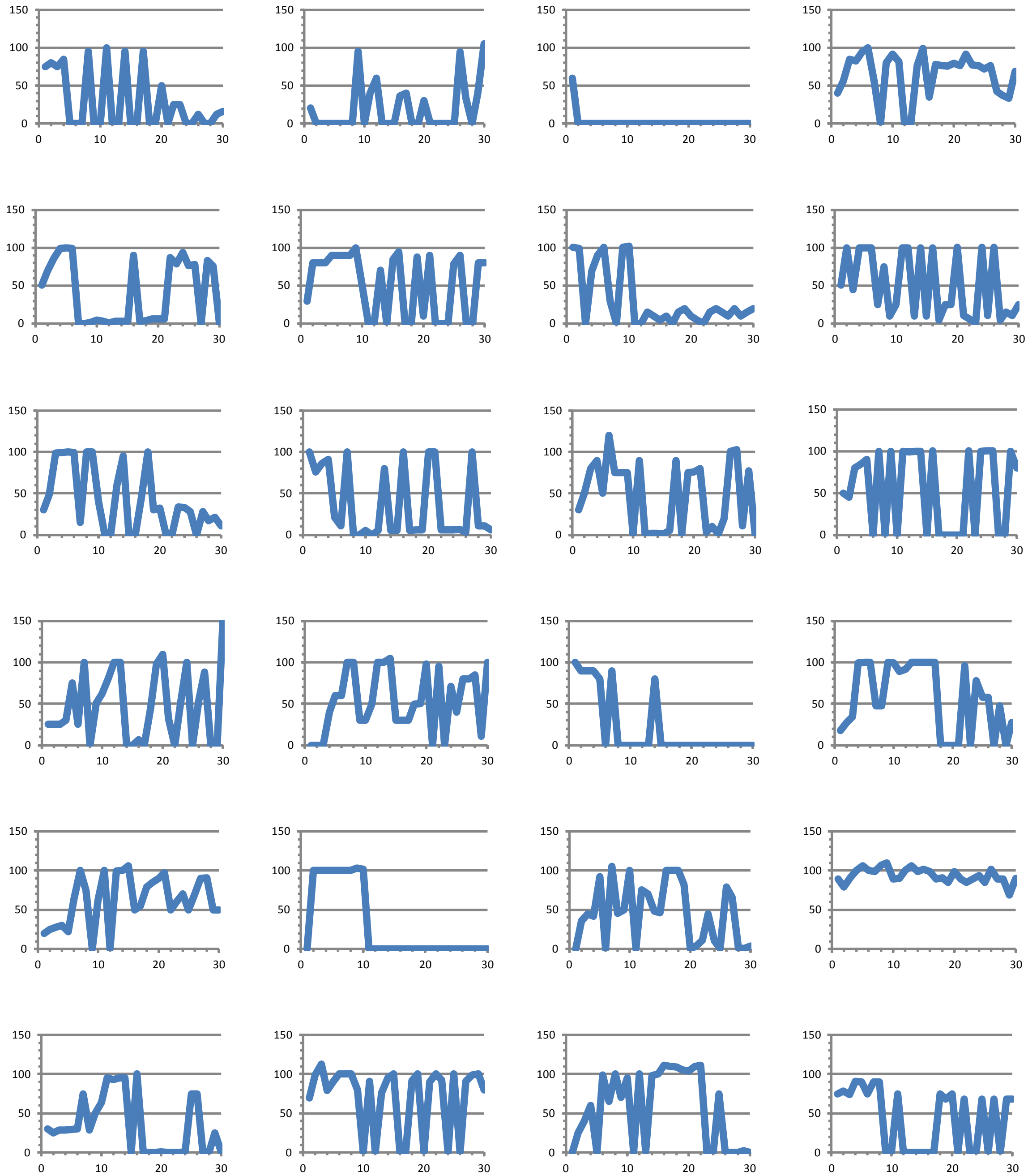


Figure 14: Individual bids in AP treatment

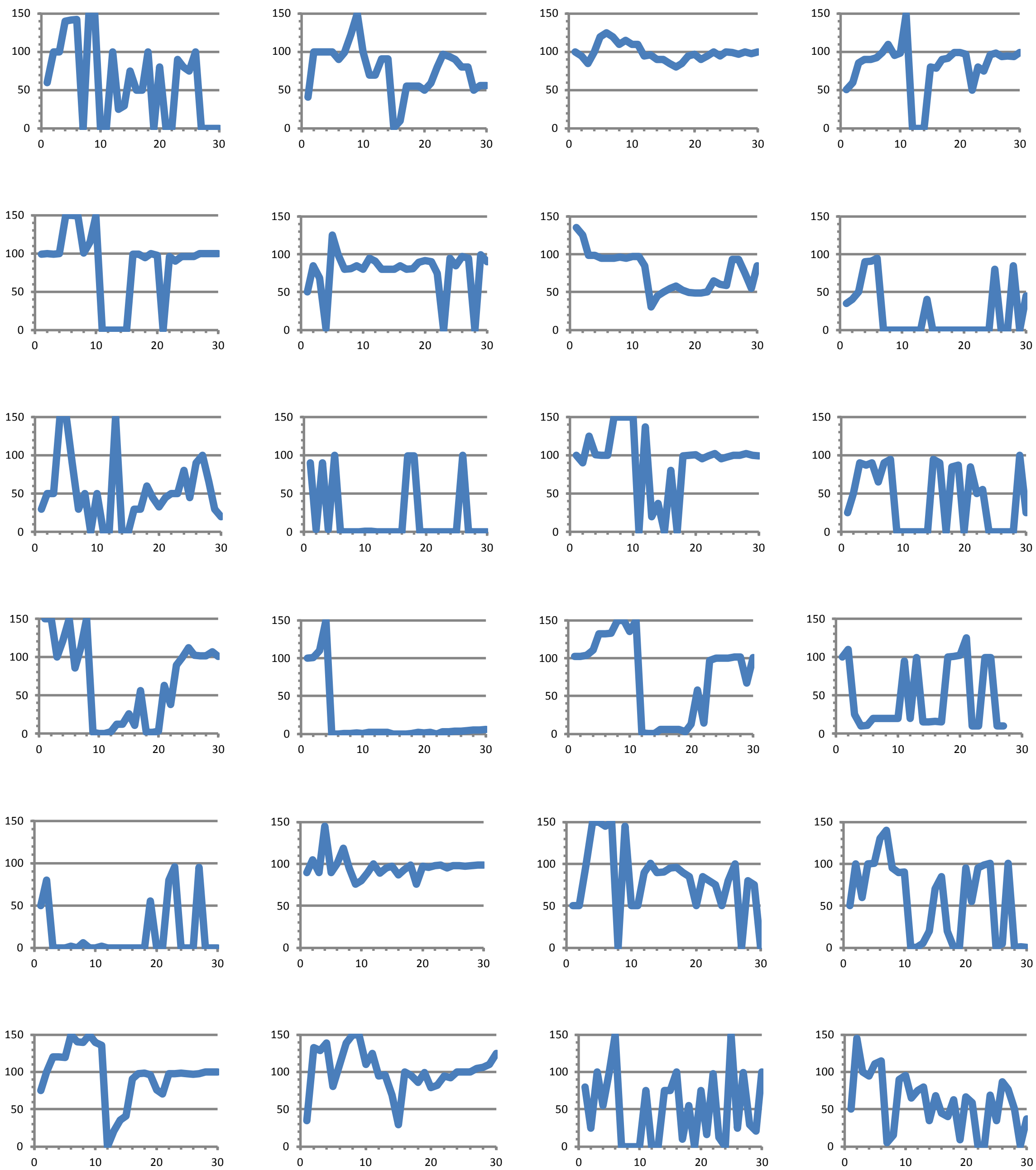


Figure 15: Individual bids in AP-N treatment

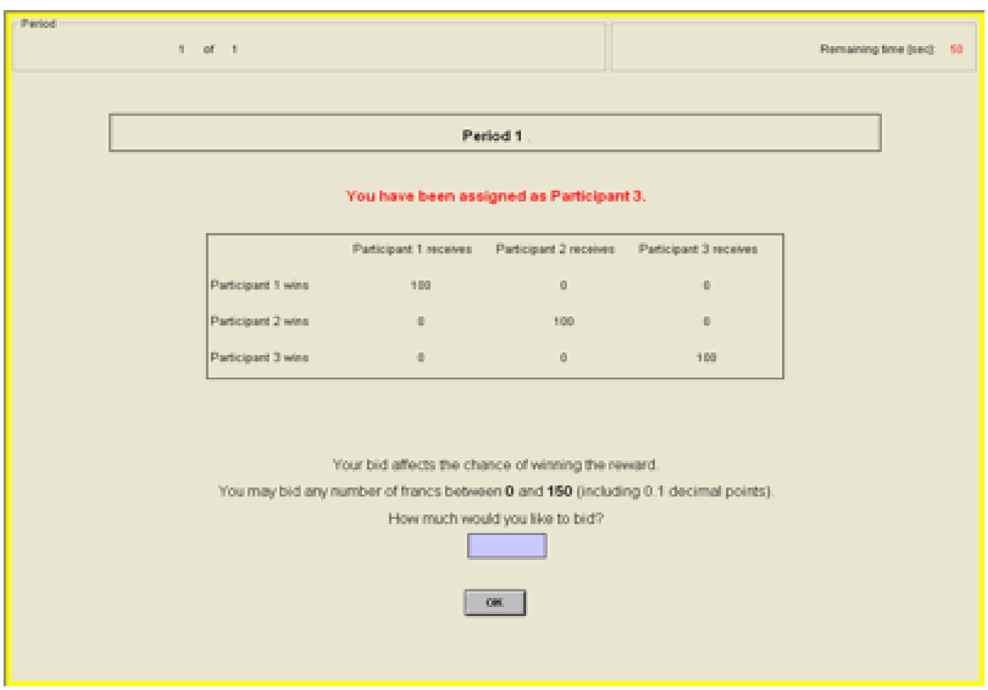
INSTRUCTIONS FOR THE DECISION PROBLEM

YOUR DECISION

The experiment consists of **30 decision-making periods**. At the beginning of the first period, you will be randomly assigned a role either as **participant 1**, **participant 2** or as **participant 3**. You will maintain the same role assignment for the entire session. Each period you will be randomly re-paired with two other participants of opposite assignments to form a **new three-person group**. So, if you are participant 1, each period you will be randomly re-paired with other participants 2 and 3. If you are participant 2, each period you will be randomly re-paired with other participants 1 and 2. If you are participant 3, each period you will be randomly re-paired with other participants 1 and 2.

Each period, you may bid for a reward. The reward is worth **100 francs**. You may bid any number between **0** and **150** (including 0.1 decimal points). An example of your decision screen is shown below.

The computer will assign the reward in your group to the participant who makes



the highest bid. So, if participant 1 bids 30 francs while participant 2 bids 30.1 francs, and participant 3 bids 20 francs then the computer will assign the reward to participant 2. In case of a tie, the computer will randomly assign the reward between the high bidders.

YOUR EARNINGS

After all three participants make their bids, *the computer will assign the reward to a participant who makes the highest bid.* Remember, the reward is worth **100 francs** to the winner. Regardless of who receives the reward, **all three participants will have to pay their bids**. Thus, the period earnings will be calculated in the following way:

If participant 1 receives the reward:

Participant 1'searnings = **100** - Participant 1'sBid

Participant 2's earnings = **0** - Participant 2's Bid

Participant 3's earnings = **0** - Participant 3's Bid

If participant 2 receives the reward:

Participant 1'searnings = **0** - Participant 1'sBid

Participant 2's earnings = **100** -Participant 2's Bid

Participant 3's earnings = **0** - Participant 3's Bid

If participant 3 receives the reward:

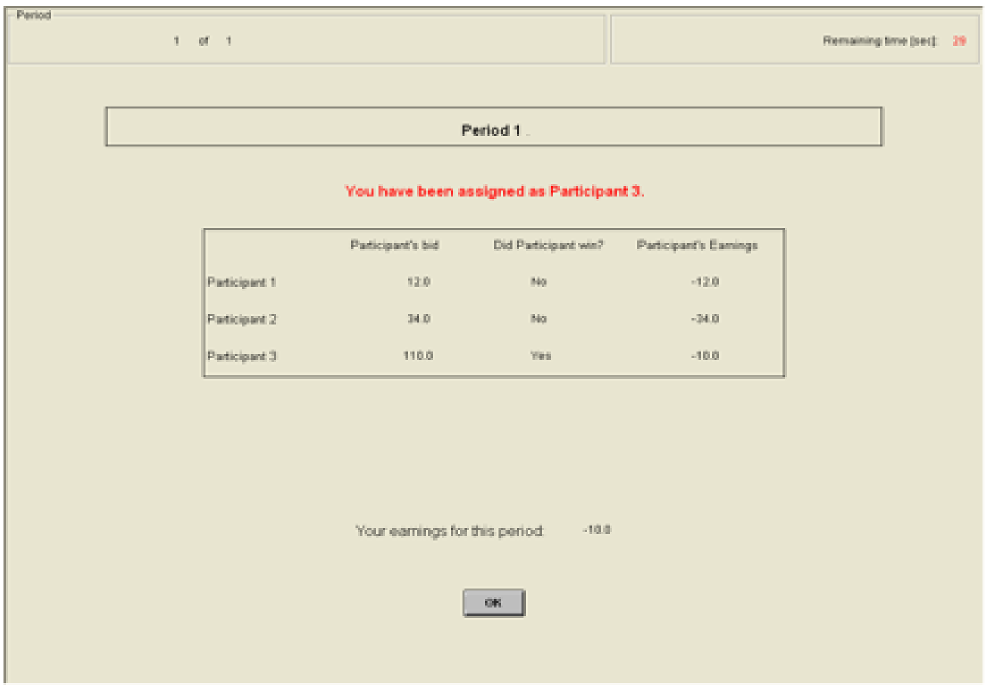
Participant 1's earnings = **0** - Participant 1's Bid

Participant 2's earnings = **0** - Participant 2's Bid

Participant 3's earnings = **100** - Participant 3's Bid

Remember you have already received a **$15.00** participation fee (equivalent to 15*25=**375 francs**). Depending on the outcome in a given period, you may receive either *positive or negative* earnings. At the end of the experiment we will randomly select **3** out of the **30** periods of the experiment for actual payment. You will sum the total earnings for these three periods and convert them to a U.S. dollar payment. If the earnings are negative, we will subtract them from your participation fee. If the earnings are positive, we will add them to your participation fee.

At the end of each period the computer will display an outcome screen for your group which shows all bids made by each participant, the participant who received the reward and your earnings for the period (an example is shown below). Once the outcome screen is displayed you should record your results for the period on your **Personal Record Sheet** under the appropriate heading.



IMPORTANT NOTES

At the beginning of the first period, you will be randomly assigned either as participant 1, participant 2 or as participant 3. You will stay in the same role assignment for the entire session of the experiment. Each period you will be randomly re-paired with two other participants of opposite assignments to form a new three-person group (1, 2, and 3). So, if you are participant 1, each period you will be randomly re-paired with other participants 2 and 3. If you are participant 2, each period you will be randomly re-paired with other participants 1 and 3. If you are participant 3, each period you will be randomly re-paired with other participants 1 and 2. All three participants will bid for a reward. The reward is worth 100 francs to the winner. The computer will assign the reward to a participant who makes the highest bid. Regardless of who receives the reward, all three participants will have to pay their bids. At the end of the experiment we will randomly select 3 of the 30 periods for actual payment using a bingo cage. You will sum the total earnings for these three periods and convert them to a U.S. dollar payment. **Are there any questions?**