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# Out-of equilibrium bids in auctions Wrong expectations or wrong bids\*

Oliver Kirchkamp<sup>†</sup>     J. Philipp Reiß<sup>‡</sup>

16th March 2008

## Abstract

Deviations from equilibrium bids in auctions can be related to inconsistent expectations with correct best replies (see Eyster and Rabin, 2005; Crawford and Iriberry, 2007) or correct expectations but small (perhaps quantal-response) mistakes in best replies (see Goeree et al., 2002).

To distinguish between these two explanations we use a novel experimental procedure and study expectations together with best replies. We extensively test the internal validity of this setup. We find that deviations from equilibrium bids do not seem to be due to wrong expectations but due to deviations from a best reply.

Keywords: Experiments, Auction, Expectations.

(JEL C92, D44)

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# 1 Introduction

Since early auction experiments by Coppinger et al. (1980) and Cox et al. (1982) it is well-known and repeatedly confirmed that bidders consistently deviate from risk neutral symmetric Bayesian Nash equilibrium (RNBNE). In the literature we can broadly distinguish between three different approaches to explain deviating bidding behaviour: Some authors propose alternative utility functions, some authors replace ex-ante (equilibrium) considerations by ex-post (learning) dynamics, and some authors study modifications of the decision making process.

To start with the first approach: a standard way to introduce an alternative utility function is to allow for risk aversion. Indeed, risk aversion explains overbidding deviations from RNBNE to some degree in first-price auctions (see, e.g., Andreoni et al., 2007; Chen and Plott, 1998; Cox et al., 1988; Kirchkamp et al., 2007). However, risk aversion does not explain all deviations addressed by the literature on auctions. Already Cox et al. (1985) find that overbidding in first-price auctions persists if bidders are paid with lottery tickets, i.e. in a situation where even the most risk averse von Neumann-Morgenstern utility maximiser behaves in a risk neutral way. Overbidding in second-price auctions (see Kagel et al., 1987; Harstad, 2000; Cooper and Fang, forthcoming) or underbidding in third price auctions (see Kagel and Levin, 1993) can not be explained by risk aversion. Furthermore, individual attitudes toward risk are not consistent over different institutions (see Isaac and James, 2000). Accordingly, recent literature suggests alternative modifications of the utility function, introducing motives like regret (see Filiz-Ozbay and Ozbay, 2007; Engelbrecht-Wiggans and Katok, 2007), or spite (Morgan et al., 2003). Finally, Ockenfels and Selten (2005) and Neugebauer and Selten (2006) introduce ex-post learning to explain bidding behaviour.

In this paper we take standard utility functions and the concept of ex-ante (equilibrium) rationality as given and, instead, focus on the derivation of equilibrium bids. A Bayesian Nash equilibrium requires that each bidder forms consistent expectations about all opponents' strategies and, based on these expectations, optimally responds with correct best replies. Deviations from equilibrium strategies can, thus, either be the result of inconsistent expectations or the result of mistakes in best replies (see Stahl and Wilson, 1995). Eyster and Rabin (2005) and Crawford and Iriberri (2007) show that simplified (and inconsistent) expectations can explain overbidding in first-price common-value auctions. Goeree et al. (2002) follow the latter approach with a model of quantal-response-equilibria. This model is based on consistent expectations and explains overbidding in first-price private-

value auctions as the result of small mistakes in forming best replies.

Since both approaches fit various experimental auction data to some degree, we find it important to investigate whether either manipulations of the process of expectation formation or refinements of best reply optimization are more promising for further theoretical developments. Indeed, Chen and Plott (1998, p. 73) suggest for first-price auctions that “the theory of beliefs and belief formation might be the most productive place to work.”

Experiments, like the one of Crawford and Iriberri (2007) or Goeree et al. (2002) observe only bids. However, in the equilibrium framework bids are the result of a two stage process: expectations together with best replies. In our paper we introduce and test a new method which allows us to measure expectations and bids together. This method allows us to gain more insight into the bidding process and to better understand to which degree mistakes in expectations and mistakes in best replies contribute to deviations from Bayesian Nash equilibria.

While we are proposing a procedure to measure expectations and bids simultaneously, we have to ask whether it is not simpler to study the two components in isolation. Imagine two hypothetical studies: In a first study participants only form expectations. The process of determining a best reply bid is computerised, controlled, and fixed. The results of this study are then compared with a second study where participants only choose strategies. Expectations are controlled through computerised opponents which follow a fixed and known strategy.

Indeed, the second step of such a separate study of expectations and best replies is feasible. Related experiments have already been carried out: Walker et al. (1987) study an experiment where participants bid against a computerised opponent. In their experiment participants are not informed about the computerised bidding function, thus, a comparison of bids with best replies is not possible. Neugebauer and Selten (2006) explore a scenario where bidders with a fixed valuation play against computerised opponents with a known distribution of bids. This setup allows to compare participants' strategies with best replies. Also Dorsey and Razzolini (2003) study the behaviour of bidders against a computerised bidder with a known bidding function. In contrast, the first step of a separate study of expectations and best replies is hard. It would require that participants describe only expectations, e.g. as a distribution of opponents' bids. Then a fixed best reply function would map these distributions into bidding functions. The computational implementation of such a best reply function is not trivial. Furthermore, it is not easy to explain such a mechanism to participants.

To avoid these complications we use a design where participants carry out both steps themselves and where we observe both steps simultaneously.

Our approach is, thus, similar to Costa-Gomes and Weizsäcker (2008) who observe actions and expectations simultaneously in  $3 \times 3$  normal form games. Their experiments suggest that strategies are typically not in line with expectations while expectations seem to resemble actual strategies fairly well.

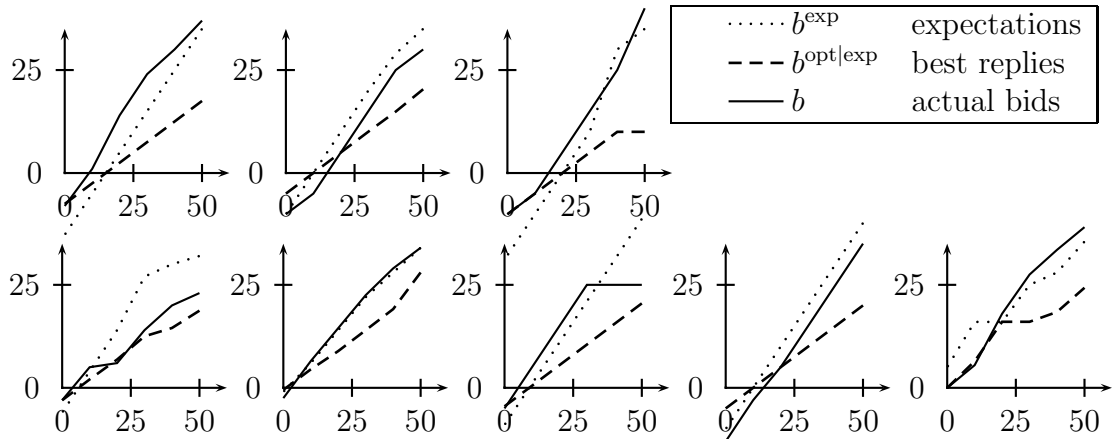
In comparison to Costa-Gomes and Weizsäcker (2008), we do not only analyse a different type of game (an auction with incomplete information and infinitely many actions instead of a  $3 \times 3$  game with complete information and a finite number of actions), we also look at a symmetric game while Costa-Gomes and Weizsäcker use asymmetric games. The advantage of using asymmetric games is that participants have to think separately about their own and their opponent's strategy. The disadvantage of using asymmetric games, when these games are complex, is that participants have to understand two complex situations simultaneously. Here, we decided to use the simpler, symmetric setup for our auctions. That means we have to take extra care in checking whether participants distinguish between their own and their opponents' strategies. The advantage of using a symmetric auction is that the already complex setup remains still manageable.

We briefly summarise the equilibrium model in section 2. The experimental treatments are discussed in section 3 and internal validity of our method is checked in section 4. We present results in section 5 and conclude in section 6.

## 2 Model

Our workhorse will be a private value first-price sealed-bid auction with two bidders  $i$  and  $j$ . This auction type is simple and still allows us to describe expectations and best replies in a non-trivial way. It might be interesting to enrich this environment by introducing common values in a later study. Here, however, we prefer the simplicity of the private value setting.

Bidders' valuations  $x_i$  and  $x_j$  are independently distributed according to a distribution function  $F(\cdot)$  which is the same for each bidder. The derivation of risk neutral symmetric Bayesian Nash equilibria is standard and reported to introduce notation. We will rely on risk neutral equilibria as a benchmark and we will use an experimental setup that eliminates a substantial part of the risk that bidders face in auctions. Bidder  $i$  with valuation  $x_i$  expects the opponent to follow a monotonically increasing bidding function  $b^{\text{exp}}(x_j)$  with inverse  $b^{\text{exp}(-1)}(\cdot)$ .



Expectations, best replies and bids are for eight bidders in period 7 of an experiment on 12 May 2005.

FIGURE 1: Examples for expectations, best replies, and bids in the experiment

If bidder  $i$  makes a bid  $b(x_i)$  then this bidder gains  $x_i - b(x_i)$  with probability  $F(b^{\text{exp}(-1)}(b(x_i)))$  and the expected profit is  $u = (x_i - b(x_i)) \cdot F(b^{\text{exp}(-1)}(b(x_i)))$ . Bidders choose their individual bidding function  $b_i$  to maximise  $u$  given their expected opponents' bidding function  $b^{\text{exp}}$ . It is straightforward to show (Vickrey, 1961) that if  $F()$  is a uniform distribution over some interval  $[0, \bar{x}]$  both bidders have a symmetric bidding function

$$b^*(x) = \frac{1}{2}x \tag{1}$$

in the symmetric equilibrium. We should note that, while there are auction situations where further asymmetric equilibria exist, the unique equilibrium in the introduced auction model is symmetric (Maskin and Riley, 2003).

The above derivation of equilibrium bids distinguishes two steps of reasoning. First bidders form expectations  $b^{\text{exp}}$  about the bidding function of their opponent. In the risk neutral Bayesian Nash equilibrium we have  $b^{\text{exp}} = b^*$ . Then bidders determine a best reply  $b^{\text{opt|exp}}$  given these expectations and play this best reply. In equilibrium also  $b^{\text{opt|exp}} = b^*$ . Figure 1 shows some examples of expected opponent's bidding functions  $b^{\text{exp}}$  from our experiment together with the best reply  $b^{\text{opt|exp}}$ , and the bids  $b$  actually taken in the experiment. The examples show a general property: In the experiment bids  $b$ , expectations  $b^{\text{exp}}$ , and best replies  $b^{\text{opt|exp}}$  typically do not coincide.

In section 3 we describe an experiment that allows us to observe the two steps of this decision process, i.e. the expectations  $b^{\text{exp}}$  (which define  $b^{\text{opt|exp}}$ ) together with actual bids  $b$ . Once we observe these two steps together, we can better understand

why bids deviate from risk neutral Bayesian Nash equilibrium bids. We will be able to distinguish between two types of bidders: bidders who form expectations which are systematically wrong ( $b^{\text{exp}} \neq b$ ) but whose best replies against these expectations are correct (similar to the bidders proposed by Crawford and Iriberri (2007)), and bidders with correct expectations who submit bids which are not best replies (i.e.  $b \neq b^{\text{opt|exp}}$ , more in line with Goeree et al. (2002)). With this exercise we do not aim to provide a complete and correct description of the thought process of real individuals. We are following the structure of equilibrium derivation within the context of expected utility theory, hence we can only find out where the standard equilibrium model of bidding behaviour provides a good approximation of human behaviour and where it does not. By decomposing this model into two steps we can, however, learn more than by only observing bids without expectations.

By observing bids and expectations together we can also take another look at models like the one proposed by Crawford and Iriberri (2007). The simplest player in their model of level- $k$  thinking, the  $L0$  player, is the starting point of a player's strategic reasoning. If this player is 'random', the player chooses all bids between the smallest possible valuation and the highest possible valuation with equal probability. If this player is 'truthful', the player always bids the own valuation. With our distribution of valuations both such types have the same distribution of bids. The best reply  $L1$  against an  $L0$  player is the equilibrium bid given by equation (1). Thus, our experiment allows to distinguish between  $L0$ ,  $L1$ , and  $L2$  and higher order players.  $L0$  players choose all bids from the possible range with equal probability in their own bidding function.  $L1$  players do the same for their expectations but choose a best reply against  $L0$  (which coincides with the equilibrium bid).  $L2$  and higher order players have equilibrium expectations and equilibrium bids.

### 3 Experimental setup

We use the strategy method to observe bidding functions in a way similar to Selten and Buchta (1999), Güth et al. (2003), Pezanis-Christou and Sadrieh (2003), Kirchkamp and Reiß (2004), and Kirchkamp et al. (2004). Other experiments that use this method (see Kirchkamp et al., 2004; Kirchkamp and Reiß, 2004) show that bidding behaviour that is observed with the strategy method is very similar to the behaviour observed with alternative methods. The strategy method



treatment	independent observations	participants
no expectations	36	330
expectations	8	74
expectations w. info	11	102

TABLE 1: Overview of treatments

allows us to observe bidding functions in much more detail. More importantly, it lends itself also to observe expectations.

To distinguish between bids and expected opponent's bids we compare three treatments:

- In one treatment we only elicit bids. This is our baseline treatment which we also call the 'no expectations' treatment. The only payoff in the treatment is the profit in the auctions.
- In one treatment we elicit bids and expectations. We call this the 'expectations' treatment. The payoff in this treatment is the profit in the auctions plus a reward for precision of expectations.
- In one treatment we elicit bids and expectations and give feedback about the precise bidding function of the opponents. We call this the 'expectations with info' treatment. As in the previous treatment the payoff in this treatment is the profit in the auctions plus a reward for precision of expectations.

Experiments were conducted between 12/2003 and 05/2005 in the experimental laboratory of the SFB 504 in Mannheim and in the experimental laboratory MaXLab in Magdeburg. A total of 506 subjects participated in these experiments. The average profit of a participant was 12.31€ with a standard deviation of 5.91€. Table 1 gives an overview. A detailed list of the sessions is provided in appendix A, the experimental procedure is described in appendix B. The software we used was z-Tree Version 3 $\alpha$  (the final version is documented in Fischbacher, 2007). In each treatment subjects first received written instructions, then they answered a quiz on the computer screen to make sure that they understood the instructions. Thereafter, they played twelve rounds of the actual experiment. In each of these rounds participants were matched randomly in groups of two. Each group participated in five simultaneous auctions. All treatments concluded with a questionnaire and the payment of subjects in cash.

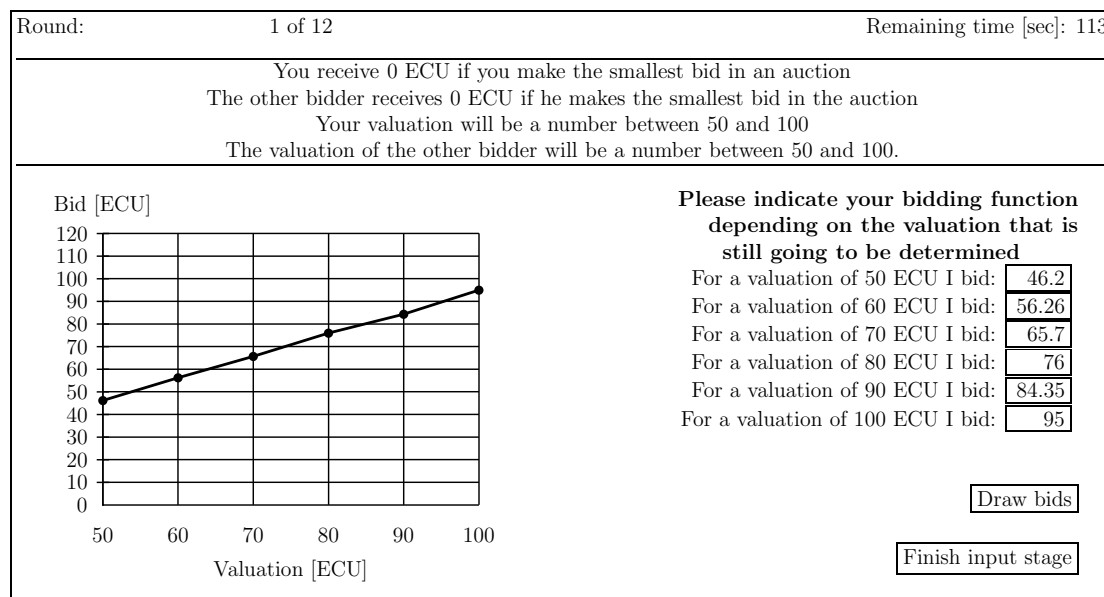


FIGURE 2: Stage 1: A typical input screen in the ‘no expectations’ treatment (translated into English)

**Input of bidding functions:** This stage was common to all treatments. Subjects would submit a bid function for a range of valuations from 50 to 100. When we present results below we will always consider normalised valuations where the valuation is in the interval  $[0, 50]$ . A typical input screen for the no expectation treatment is shown in figure 2. A typical input screen for the two treatments with expectations is shown in figure 3.

In each round participants enter bids for six valuations which are equally spaced between 50 and 100. Bids for all other valuations are interpolated linearly.

**Auction feedback:** When all participants have determined their bidding functions they move to the auction feedback stage. In this stage they play five independent auctions, i.e. the computer draws five pairs of random and independent valuations for each pair of participants. In each of these five independent auctions the winner is determined and the profit of each player is calculated. The sum of the profit of these five auctions is the total auction profit from this round. We play five auctions for two reasons: First, multiple auctions and, hence, multiple valuations, may help participants to think carefully about all parts of their bidding function. Second, and more importantly, playing multiple auctions helps us to reduce a substantial part of the risk. Kirchkamp, Reiß, and Sadrieh (2007) systematically explore the

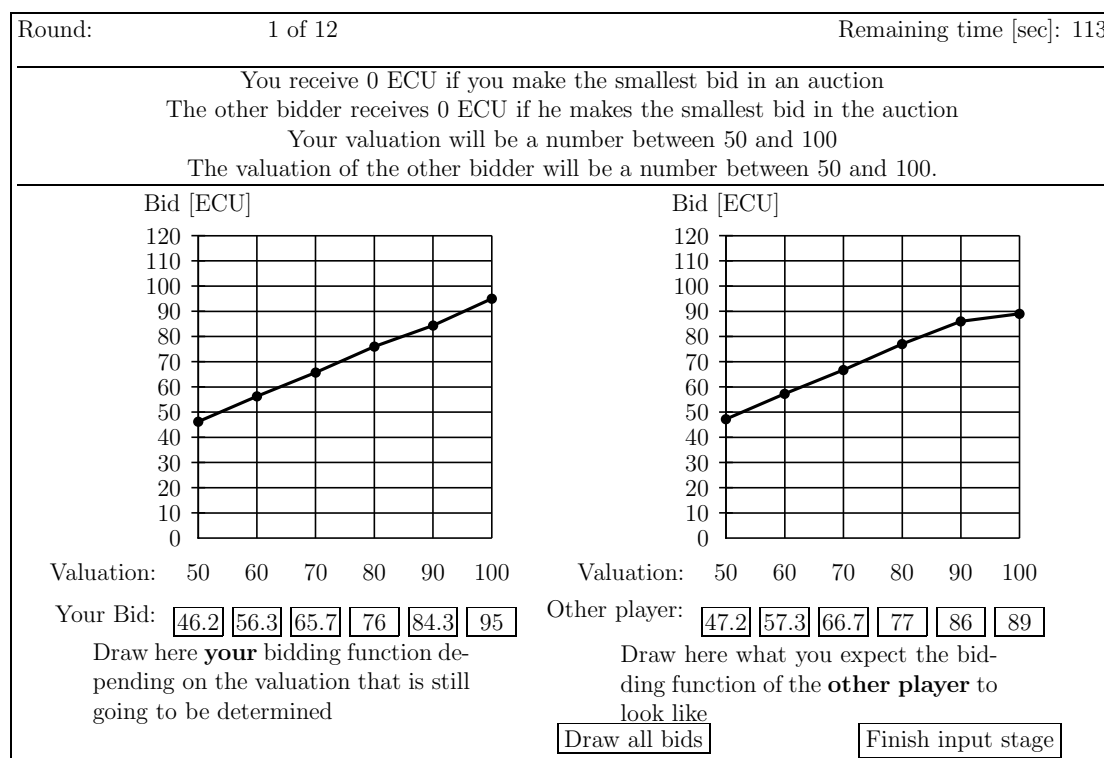


FIGURE 3: Stage 1: A typical input screen in the two ‘expectations’ treatments (translated into English)

approach of playing multiple auctions with a given bidding function and find that playing multiple auctions, indeed, makes bidders behave in a more risk neutral way. They also find that already a small number of auctions played eliminates a substantial part of the risk. To keep things simple we rely on only 5 auctions in this experiment. A typical feedback screen is shown in figure 4.

**Expectation feedback:** In the expectation treatments players get feedback about their expectations in the last stage of each round.

- In the baseline treatment the last screen in each period only shows the total payoff of the current round.
- In the expectation treatment with info the last screen in each period looks like the one shown in figure 5. A graph on the left shows the expected bid and, additionally, also the actual bid of the opponent. A small table on the right summarises the auction profit, the average difference between the expected bid and the actual bid, and the total payoff.

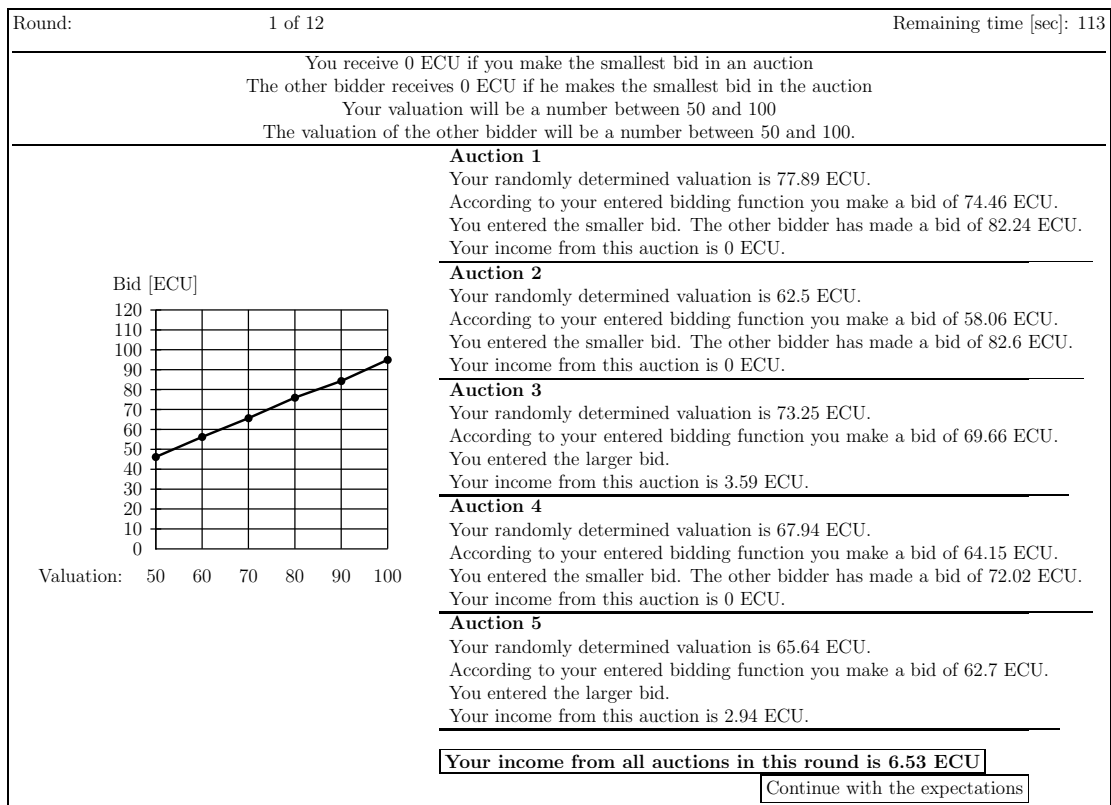


FIGURE 4: Stage 2: A typical feedback screen (translated into English)

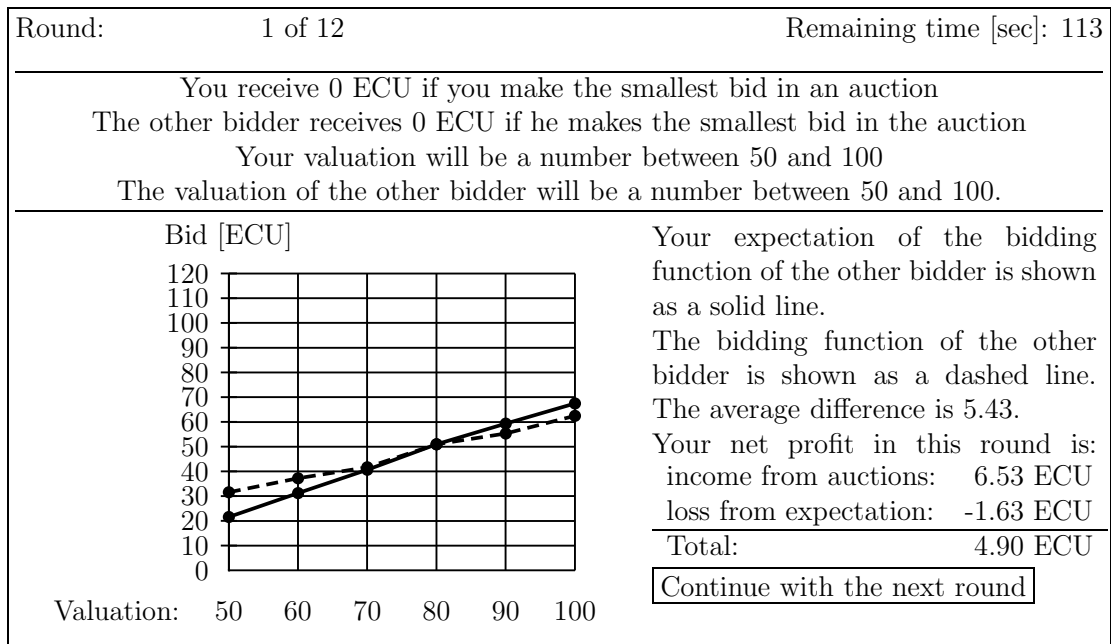


FIGURE 5: Stage 3: Expectation feedback in the expectation with info treatment

- In the expectation treatment (without info) the only difference is that the graph on the left displays only the player's own expectation and not the actual bidding function of the opponent.

To pay participants for correct expectations in the expectation treatments we use the average of absolute differences between the actual bid of the opponent and the expected bid at the six points where bids and expectations were made.

$$\frac{1}{6} \sum_{x \in \{50,60,70,80,90,100\}} |b_x - b_x^e|$$

This average deviation is multiplied with a conversion factor of 0.3 and subtracted from the auction profit.

**Point expectations** In the above discussion we made the implicit assumption that individuals expect their opponents to have one specific bidding function  $b^{\text{exp}}$ . We call this a point expectation. What, if a player is uncertain about the bidding function of the opponent? A player might, e.g., expect to face an opponent with a bidding function  $b_1^{\text{exp}}$  with probability  $\frac{1}{2}$  and to face an opponent with another bidding function  $b_2^{\text{exp}}$  again with probability  $\frac{1}{2}$ . A player might have an entire distribution over the space of all opponent's bidding functions in mind. How should such a player behave in our experiment? Since we are paying players according to their absolute deviations from the opponent's bidding function, players should report as expectations a least absolute deviation estimator, which is the median expected bid. When bidding under uncertainty about the opponent's bids, bidders are only interested in the distribution over their opponent's bids. An uncertain bidder who does not know the opponent's bids faces the same situation as a certain bidder who plays against the average bidding function (where the averages are taken along the opponent's bids). Thus, as long as the difference between median and mean bidding functions is small, the problem should be small. To assess the order of magnitude of the problem at least approximately, let us assume that bidders apply the true distribution of bidding functions. Indeed, this distribution has a small negative skew. Medians are smaller than means by about 1.8% of the range of valuations (the size of the deviation does not depend much on the valuation). Thus, any deviation between reported expectations and bids of that magnitude is still perfectly rational. We will, however, find that deviations are substantially larger.

Even if mean expected bids deviate substantially from median expected bids

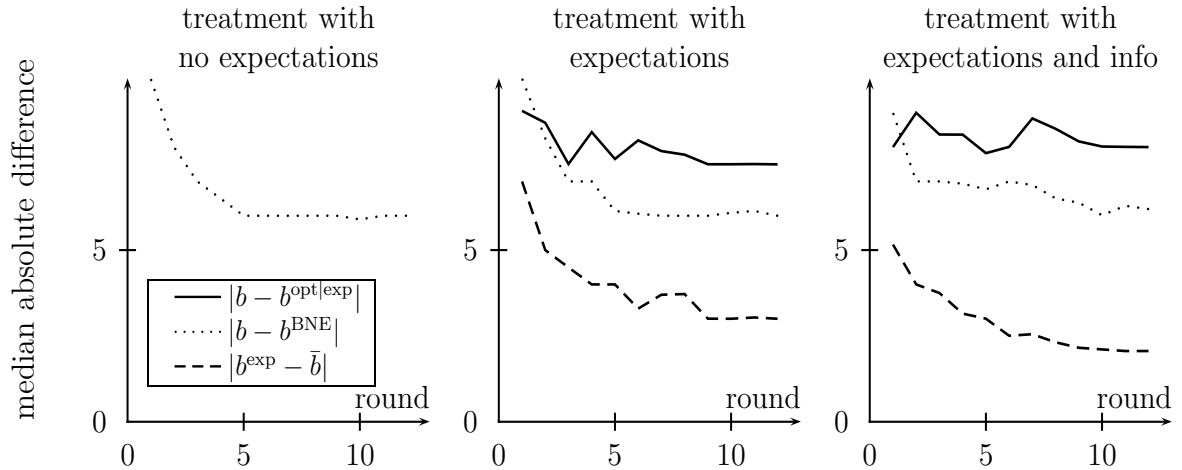


FIGURE 6: Convergence of bids and expectations

the incentive to hedge is small. The loss for reporting other than median expectations and optimising against other than mean expectations is large, and the profit from hedging is very low unless the distribution is extremely asymmetric and participants are very risk averse. Hence, we do not expect hedging to be a problem. In the following we will disregard the problem of distributions of expectations and assume that bidders have point expectations of opponent's bidding functions.

## 4 Method and internal validity

Given the novelty of our experimental design we check whether we actually measure what we intend to measure. Do participants understand the experiment, have they carefully thought about their expectations, and do they take their expectations into account when constructing their bids? To gain a first impression, figure 1 on page 4 shows some examples for bids and expectations from the experiments. In section 4.1 we check convergence of behaviour. Section 4.2 investigates treatment effects. In section 4.3 we see whether participants in the experiments form reasonable expectations and section 4.4 checks whether bids follow actually best replies given these expectations. Only after all of these robustness checks are carried out with satisfying results we present results in section 5.

### 4.1 Convergence

The experiment is divided into 12 rounds. In figure 6 we illustrate convergence of bids and expectations in the three different treatments.

A natural reference point for players' bids  $b$  are risk neutral Bayesian Nash equilibrium bids  $b^{\text{BNE}}$ . If players follow the equilibrium then the absolute difference  $|b - b^{\text{BNE}}|$  should be zero. The dotted line in figure 6 shows the median of  $|b - b^{\text{BNE}}|$  over time. While the distance between experimental bids and equilibrium decreases during the first three or four rounds of the experiment it does not change very much during the second half of the experiment and remains at a high level. We take this as good news and an indication that, after a few initial rounds, players understand the experiment.

Another ingredient of players' behaviour is formation of expectations. Are expectations correct? If they are not correct, are they increasing in precision? A payoff maximising player in our experiment who knows the true distribution function of all bidding functions will report the median bidding function as the expected bid. In figure 6 we compare the median bid  $\bar{b}$  with the expectation  $b^{\text{exp}}$ . The dashed line shows the median of  $|b^{\text{exp}} - \bar{b}|$ . If expectations were perfect then this difference should be zero. Again, the difference decreases during the first few rounds of the experiment and becomes more stable towards the end.

Based on bidders' expectations  $b^{\text{exp}}$  we can, for each bidder and each period, determine a best reply bid  $b^{\text{opt|exp}}$  (examples are shown in figure 1 on page 4). With players who always choose a bid  $b$  which is a best reply  $b^{\text{opt|exp}}$  given their expectations the difference  $|b - b^{\text{opt|exp}}|$  should be zero. The solid line in figure 6 shows the median of  $|b - b^{\text{opt|exp}}|$ . Also this difference remains stable during the second half of the experiment.

We discuss expectations  $b^{\text{exp}}$  and bids  $b$  below in more detail. The purpose of this section is to show convergence of our data. In the following we restrict our analysis to periods 7 to 12 where behaviour is fairly stable. However, all main results do not change if all periods of the experiment are included.

## 4.2 Treatment effects

Does the method that we introduce to measure behaviour change behaviour? Figure 7 compares median overbidding under the three different treatments. In equilibrium we should observe no overbidding, i.e. a horizontal line. The increasing lines for the three treatments confirm a finding reported in many previous studies: there is overbidding for large valuations in all treatments. The good news is that median bids are very similar under all three treatments. We see that overbidding is, if at all, even more pronounced under the expectation with info treatment. To test this formally we look at the difference between actual bids  $b(x)$  under

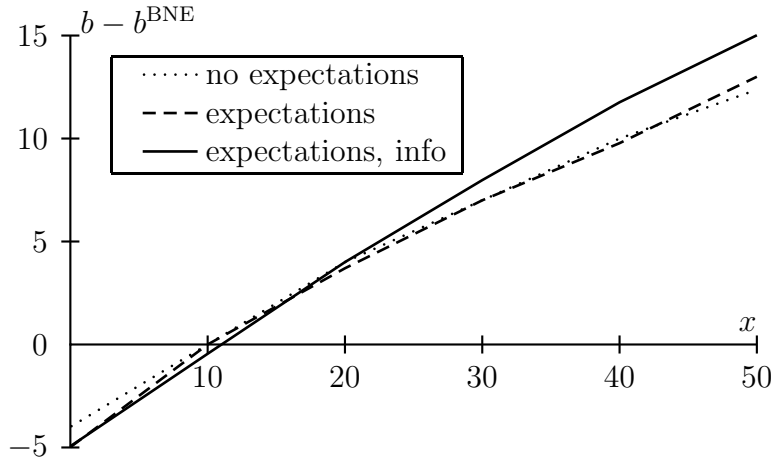


FIGURE 7: Median overbidding

expectations; 8 independent obs.					
	$\beta$	$\sigma$	$t$	$P_{>t}$	95% conf. interval
$x$	-.0016	.02209	-0.072	0.944	-.05384, .05064
$\beta_0$	-.8499	.87882	-0.967	0.366	-2.928, 1.2282
expectations, info; 11 independent obs.					
	$\beta$	$\sigma$	$t$	$P_{>t}$	95% conf. interval
$x$	.04762	.02164	2.200	0.052	-.00061, .09584
$\beta_0$	-1.7251	.39805	-4.334	0.001	-2.612, -.83819

TABLE 2: Estimation of equation (2) for the two expectation treatments

the expectation treatments and median bids  $\bar{b}^{\text{noexp}}(x)$  for different valuations  $x$  in the no expectation treatments.<sup>1</sup> If introducing expectations in the experiment does not affect bids these differences should be zero. We estimate the following equation:

$$b(x) - \bar{b}^{\text{noexp}}(x) = \beta_x x + \beta_0 \tag{2}$$

Estimation results are given in table 2.<sup>2</sup> We see that introducing expectations without information about the bidding function of the opponent does not have a significant impact. Introducing expectations with information about the op-

<sup>1</sup>We did the same exercise with mean bids and obtain basically the same result. Since medians are less vulnerable to outliers we are concentrating on medians here. The structure of equation (2) does not require overbidding to be linear in  $x$  (though it requires the treatment effect to be linear). One can impose such linear relationship between  $x$  and the amount of overbidding and obtains very similar results.

<sup>2</sup>When calculating levels of standard deviations and levels of significance we have to take into account that observations within our experimental sessions may be correlated. We can safely assume that covariances of observations from different sessions are zero. Covariances of observations from the same experiment are replaced by the appropriate product of the residuals (Rogers, 1993). We will use this approach throughout the paper to calculate standard errors.



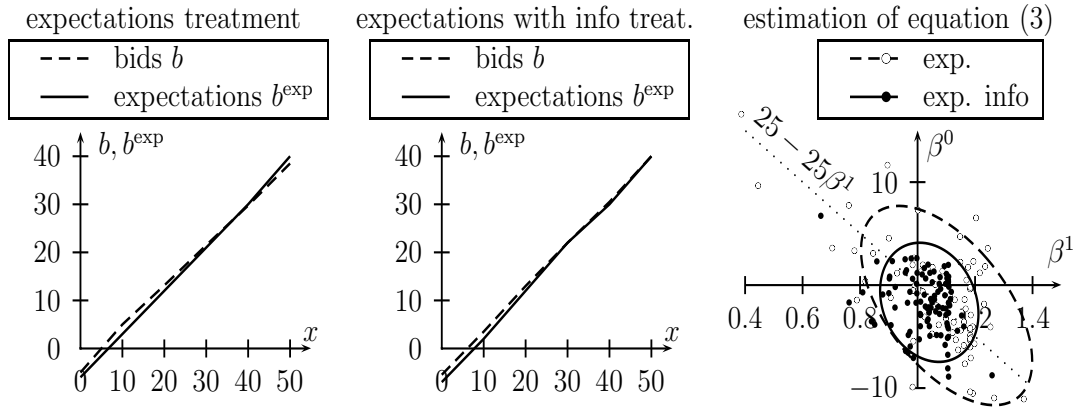


FIGURE 8: Median bids, median expectations, and estimation of equation (3)

ponent’s bidding function significantly increases overbidding for large valuations measured as  $\beta_x$  and also increases underbidding for small valuations ( $\beta_0$ ). Thus, at least for the treatment with information we do find an (albeit small) treatment effect. However, the effect does not diminish the deviation from symmetric risk neutral Bayesian Nash equilibria. On the contrary, in this treatment the deviation from equilibria is even stronger.

### 4.3 Quality of expectations

In our experiment subjects have an incentive to submit precise expectations. The larger the deviation of their expectation from their opponent’s true bidding function, the smaller is their payoff. To analyse the quality of our participants’ expectations we proceed in two steps: First, we show that expectations are, indeed, close to median bids. Second, we show that expectations react to changes of bids.

The left part of figure 8 shows median bidding functions and medians of expected bids for both expectation treatments. We see that median expectations do not deviate much from median bids. To allow for individual heterogeneity and as a more formal test we determine for each period, treatment, and valuation the median bidding function  $\bar{b}_t(x)$ . Ideally, this is what participants should expect in this period.<sup>3</sup> For each individual  $i$  we estimate

$$b_i^{\text{exp}}(x) = \beta_i^1 \bar{b}_t(x) + \beta_i^0 + u. \quad (3)$$

<sup>3</sup>As above we did the same exercise with mean bids to obtain basically the same result. Since medians are less vulnerable to outliers we are concentrating on medians here.

treatment	n	slope				mean			
		$\beta^1 - 1$	t	$P_{> t }$	$P_{\text{bin}}$	$\beta^0 - 25 + 25\beta^1$	t	$P_{> t }$	$P_{\text{bin}}$
exp.	8	.0736	2.591	0.036	0.070	.5644	2.009	0.085	0.727
exp., info	11	.0291	2.009	0.072	0.227	-1.023	-1.975	0.077	0.549
all	19	.0478	3.158	0.005	0.019	-.3557	-0.976	0.342	1.000

TABLE 3: Testing coefficients from equation (3)

With consistent expectations we have  $\beta^1 = 1$  and  $\beta^0 = 25 - 25\beta^1$ . The right part of figure 8 shows the estimated coefficients for each individual separately together with 95% confidence ellipses.<sup>4</sup> Table 3 reports  $t$ -tests and binomial tests for  $\beta_i^1 = 1$  (slope of equation (3) is one) and for  $\beta^0 = 25 - 25\beta^1$  (mean expectation equals mean bid). Expected bidding functions are slightly steeper than actual bidding functions, the difference is also significant, but small.

The estimation of equation (3) quantifies the quality of expectations, but it does not reveal the causality between bids and expectations. Do participants really have a good model of the behaviour of the population in mind and use this to form good expectations, or do participants follow a naïve procedure: mainly copying the own bid into the expectation graph?

To measure how opponents' bids affect expectations we use the data from our 'expectation with info' treatment. Since bidders are matched in every period with a new random opponent, the bidding function of the opponent in the current round is not a perfect predictor for the opponent in the next round. Nevertheless, it provides new information about the distribution of bidding functions in the population. We use the opponent's bid in this treatment as an explanatory variable for expectations and estimate the following equation in first differences<sup>5</sup>:

$$\Delta_t b_i^{\text{exp}} = \beta_j \cdot \Delta_{t-1} b_j + \beta_0 + u \quad (4)$$

The magnitude of  $\beta_j$  in equation (4) should depend on the prior expectations of the bidder. A bidder with no prior expectations should have a  $\beta_j$  close to one. A bidder with strong prior expectations who is convinced that nothing new can be learned from the current opponent should have a  $\beta_j = 0$ . The result of estimating coefficient  $\beta_j$  along with the results of a  $t$ -test and a binomial test, are reported in table 4. The coefficient of  $\Delta_{t-1} b_j$  is positive and significantly different from

<sup>4</sup>Robust covariances are obtained with R's `cov.tob` command. The confidence region is based on the standard  $F$  statistics.

<sup>5</sup>Since  $b_i^{\text{exp}}$  and  $b_j$  are possibly correlated, we can not use absolute values.

	$n$	$\beta_j$	$t$	$P_{> t }$	$P_{\text{bin}}$
	11	.0373	2.916	0.015	0.065

TABLE 4: Test for the coefficient of  $\Delta_{t-1}b_j$  in equation (4)

	$\beta$	$\sigma$	$t$	$P_{>t}$	95%conf. interval
$\Delta_{t-1}b_j$	.02566	.00826	3.106	0.011	.00725, .04406
$\Delta_t b_i$	.4922	.15471	3.181	0.010	.14749, .83692
$\beta_0$	.23205	.04485	5.174	0.000	.13211, .33198
independent obs.	11				

TABLE 5: Estimation of equation (5)

zero. Thus, changes in an opponent’s individual bidding function seem to have an effect on a bidder’s expectations for the next period.

Could it be that a positive coefficient of  $\Delta_{t-1}b_j$  in equation (4) arises due to an indirect effect? Naïve bidders see opponents’ bids rise, in response they increase their own bids (without thinking about expectations), and, when asked about expectations, they simply use their own bids as expectations. To test this, we add  $\Delta_t b_i$  as an explanatory variable in equation (5).

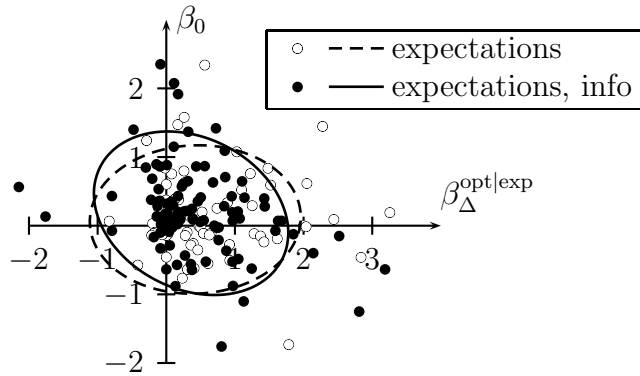
$$\Delta_t b_i^{\text{exp}} = \beta_j \cdot \Delta_{t-1}b_j + \beta_i \cdot \Delta_t b_i + \beta_0 + u \tag{5}$$

Table 5 reports estimation results. We see that, even if we allow bidders to follow the above naïve strategy, the coefficient of  $\Delta_{t-1}b_j$  is still significantly positive, i.e. bids of opponents do directly affect expectations. A positive and significant coefficient for  $\Delta_t b_i$  is no confirmation of the above naïve model. Also with rational players there should be a relationship between  $b$  and  $b^{\text{exp}}$ .

To summarise: We find that bidders in the experiment form expectations which are close to actual bids. These expectations follow to a significant amount the available information about actual opponents’ bids.

#### 4.4 Quality of reactions to expectations

Whatever the expectations are, can we assume that bidders submit optimal bids given their expectations? To address this question we construct for each bidder and each period the best reply given this bidder’s expectations  $b^{\text{exp}}(x)$ . We call this best reply  $b^{\text{opt|exp}}(x)$ . Since in our experiment bids are stepwise linear with support points  $\{0, 10, 20, 30, 40, 50\}$  we use a numerical procedure to find  $b^{\text{opt|exp}}(x)$ . Some examples are shown in figure 1 on page 4. We compare actual bids  $b$  with best



Joint distribution of  $\beta_{\Delta}^{\text{opt|exp}}$  and  $\beta_0$  from equation (6) and 95% confidence ellipses.

FIGURE 9: Estimation of equation (6)

	$n$	$\beta_{\Delta}^{\text{opt exp}}$	$t$	$P_{> t }$	$P_{\text{bin}}$
info	8	.5698	5.373	0.001	0.008
info, exp.	11	.4357	4.243	0.002	0.001
all	19	.4921	6.599	0.000	0.000

TABLE 6: Test of  $\beta_{\Delta}^{\text{opt|exp}} = 0$  from equation (6)

replies  $b^{\text{opt|exp}}$  and estimate

$$\Delta b_i(x) = \beta_{\Delta}^{\text{opt|exp}} \cdot \Delta b^{\text{opt|exp}} + \beta_0 + u. \quad (6)$$

A rational bidder should have  $\beta_{\Delta}^{\text{opt|exp}} = 1$ . A bidder who is slow in adapting and who also takes past experience into account should have  $\beta_{\Delta}^{\text{opt|exp}} < 1$ . Results of estimating equation (6) for each bidder individually are shown in figure 9. Outliers have been eliminated using Hadi's (1994) method. Table 6 provides results of a  $t$ -test and a binomial test. The coefficient  $\beta_{\Delta}^{\text{opt|exp}}$  is significantly positive, i.e. bidders do take the best reply  $b^{\text{opt|exp}}$  into account when choosing their bid  $b$ .

## 5 Results

In the previous section we have tested the reliability of our experimental framework. In equations (4) and (5) we have studied how actual bids affect expectations. In equation (6) we have checked how expectations affect actual bids.

In this section we compare bids and expectations with Bayesian Nash equilibrium. The explanatory variable in our regression is no longer the actual bid

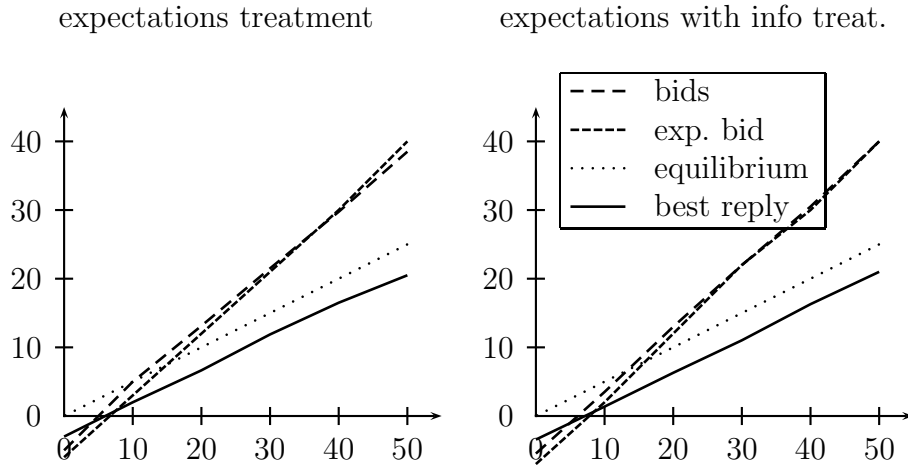


FIGURE 10: Median bids and median best replies

$b$  or the actual expectation  $b^{\text{exp}}$ , as it was in the previous section, but rather what bidders should do if they followed equilibrium bidding functions and best replies, i.e.  $b^{\text{BNE}}$  and  $b^{\text{opt|exp}}$ . As already stated, we do not aim at providing a complete and correct description of the thought process of real individuals. We are restricting ourselves to the derivation of Bayesian Nash equilibrium. In a first step we want to explore what happens on the way from  $b^{\text{BNE}}(x)$  to  $b^{\text{opt|exp}}$ . In a second step we want to understand how  $b^{\text{opt|exp}}$  translates into  $b$ . We want to measure whether deviations between actual and equilibrium bids are rather due to non equilibrium expectations or whether they are due to wrong best replies. We estimate the following two equations:

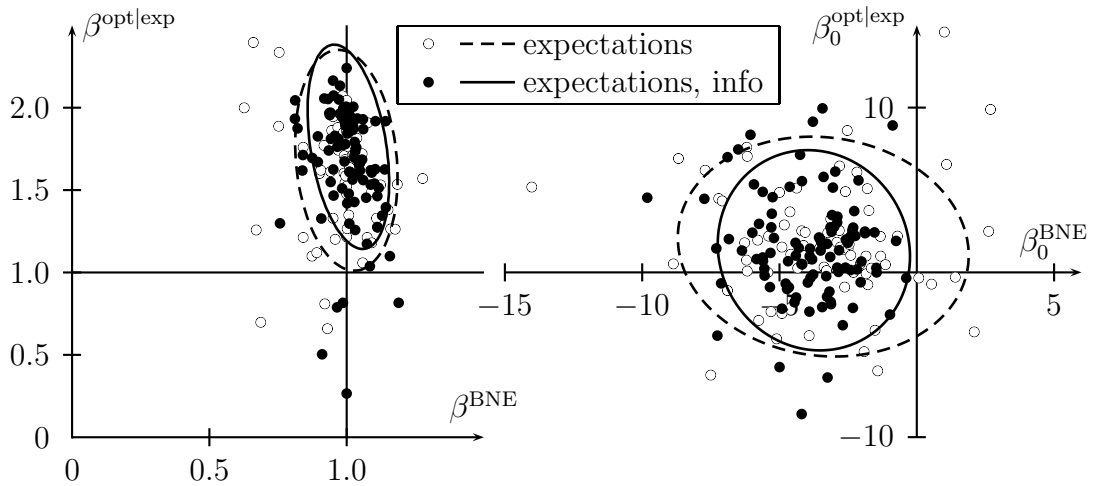
$$b_i^{\text{opt|exp}}(x) = \beta^{\text{BNE}} \cdot b^{\text{BNE}}(x) + \beta_0^{\text{BNE}} + u \quad (7)$$

$$b_i(x) = \beta^{\text{opt|exp}} \cdot b_i^{\text{opt|exp}}(x) + \beta_0^{\text{opt|exp}} + u \quad (8)$$

In equation (7) we use the best reply bid  $b^{\text{opt|exp}}(x)$  as the explanatory variable. If participants expect that their opponents use Bayesian Nash equilibrium bids, then  $\beta^{\text{BNE}} = 1$  and  $\beta_0^{\text{BNE}} = 0$ .

In equation (8) we regress the actual bid  $b_i(x)$  on the best reply bid  $b^{\text{opt|exp}}(x)$ . If a player chooses always the best reply given the expected opponent's bid then  $\beta^{\text{opt|exp}} = 1$  and  $\beta_0^{\text{opt|exp}} = 0$ .

Figure 11 shows the distribution of the estimated coefficients. Table 7 provides  $t$ -tests and binomial tests. Let us start with equation (7), the relation between expectations and equilibrium bids. We see that  $\beta^{\text{BNE}}$  is closely centered around one, though the constant  $\beta_0^{\text{BNE}}$  is significantly smaller than zero. What we estim-



The coefficients of the linear terms are shown on the left, those of the constants are on the right. The ellipses show a 95% confidence region.

FIGURE 11: Estimating equations (7) and (8).

	$n$	$\beta^{\text{BNE}} - 1$	$t$	$P_{> t }$	$P_{\text{bin}}$	$\beta_0^{\text{BNE}}$	$t$	$P_{> t }$	$P_{\text{bin}}$
exp.	8	-.0167	-1.254	0.250	0.727	-3.461	-8.635	0.000	0.008
exp., info	11	.0021	0.201	0.844	0.549	-3.891	-23.516	0.000	0.001
all	19	-.0058	-0.694	0.497	0.359	-3.711	-19.178	0.000	0.000
	$n$	$\beta^{\text{opt exp}} - 1$	$t$	$P_{> t }$	$P_{\text{bin}}$	$\beta_0^{\text{opt exp}}$	$t$	$P_{> t }$	$P_{\text{bin}}$
exp.	8	.6297	14.400	0.000	0.008	1.774	4.207	0.004	0.070
exp., info	11	.6943	13.833	0.000	0.001	1.5	3.962	0.003	0.001
all	19	.6671	19.569	0.000	0.000	1.615	5.846	0.000	0.000

TABLE 7: Testing coefficients from equations (7) and (8) against equilibrium values

ate for  $\beta^{\text{BNE}}$  and  $\beta_0^{\text{BNE}}$  is also reflected in the median best replies in figure 10: The solid line, which shows the median of the best replies, is almost parallel to the equilibrium bid (dotted line), but slightly below. In other words: Bidders do seem to deviate in their expectations consistently from equilibrium bids. However, the deviation we find would rather explain underbidding, not overbidding. How can it be, then, that most experimental bids are over, and not under the equilibrium bids? The reason for overbidding emerges if we look at the estimation results for equation (8). In figure 11 we clearly see that  $\beta^{\text{opt|exp}}$  is larger than one for most bidders. The constant  $\beta_0^{\text{opt|exp}}$  is close to zero. This observation is confirmed by the tests in table 7.

Let us summarise: We find that there are two effects which determine bidding behaviour. First: Bidders' expectations are fairly accurate (see section 4.3). A

best reply to these expectations leads to underbidding. Second: Bids are not best replies to bidders' expectations. This leads to overbidding. Since the second effect is stronger than the first one we observe that in the end most bids exceed equilibrium bids.

## 6 Concluding remarks

In this paper we investigate whether systematic deviations from equilibrium bidding behaviour in auctions are rather due to wrong expectations or due to wrong best replies given these expectations. The first explanation is put forward by Eyster and Rabin (2005) and Crawford and Iriberry (2007), the second by Goeree et al. (2002). Both explanations fit bidding behaviour in experiments. To distinguish between these explanations we propose an experiment where we can observe expectations and bids simultaneously. To keep things simple we use the context of a private value first-price sealed-bid auction.

Given the novelty of the approach we have checked carefully the internal validity of our setup. We have found that the expectations we measure are reliable, and that expectations also react to information in a reasonable way.

The main result was presented in section 5: Both approaches that we mentioned capture a part of the truth. Bidders make systematic mistakes in forming their expectations and in determining their strategy. However, we found that most of the deviations from equilibrium bids are not related to wrong expectations but to deviations from the best reply against these expectations.

Our results for first-price auctions complement, thus, the findings of Costa-Gomes and Weizsäcker (2008) for  $3 \times 3$  games: In both situations, ours and theirs, expectations resemble actual strategies fairly well. In both situations, however, strategies are not best replies to expectations.

Our results also support the standard approach to explain deviations from risk neutral Bayesian Nash equilibrium bids. Risk aversion, regret (see Filiz-Ozbay and Ozbay, 2007), and spite (Morgan et al., 2003) are explanations that base on expectations which are correct. We can show that, indeed, the major part of the deviation from standard equilibrium is not due to wrong expectations but happens on the reply side.

While Crawford and Iriberry's (2007) model of level- $k$  thinking can explain bids or expectations when these are measured in isolation, we see that when we measure bids and expectations together their combination is not consistent with

any level of  $k$ .

When we observe accurate expectations and inaccurate best replies in the lab we should keep in mind that forming precise expectations about opponents' bids might be easier in the lab than in real world auctions. Still, if the difference between bids and best replies is large in the lab we should expect this difference to be significant in the field as well.

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## A List of independent observations

date	treatment	place	min.bid	participants
20040517-12:21-0	no expectations	Mannheim	-50	8
20040517-12:21-1	no expectations	Mannheim	-50	6
20040517-17:17-0	no expectations	Mannheim	-50	8
20040517-17:17-1	no expectations	Mannheim	-50	8
20031211-18:23-0	no expectations	Mannheim	0	14
20031212-10:45-0	no expectations	Mannheim	0	14
20040519-15:53-0	no expectations	Mannheim	0	8
20040519-15:53-1	no expectations	Mannheim	0	10
20050414-08:55-0	no expectations	Magdeburg	0	10
20050414-08:55-1	no expectations	Magdeburg	0	10
20050414-13:17-0	no expectations	Magdeburg	0	10
20050414-13:17-1	no expectations	Magdeburg	0	10
20050613-08:39-0	no expectations	Magdeburg	0	10
20050613-08:39-1	no expectations	Magdeburg	0	8
20050613-10:27-0	no expectations	Magdeburg	0	10
20050613-10:27-1	no expectations	Magdeburg	0	8
20050613-14:39-0	no expectations	Magdeburg	0	10
20050613-14:39-1	no expectations	Magdeburg	0	8
20050614-08:45-0	no expectations	Magdeburg	0	8
20050614-08:45-1	no expectations	Magdeburg	0	8
20050614-10:41-0	no expectations	Magdeburg	0	10
20050614-10:41-1	no expectations	Magdeburg	0	8
20050614-14:41-0	no expectations	Magdeburg	0	10
20050614-14:41-1	no expectations	Magdeburg	0	10
20050615-08:49-0	no expectations	Magdeburg	0	10
20050615-08:49-1	no expectations	Magdeburg	0	8
20050615-10:41-0	no expectations	Magdeburg	0	10
20050615-10:41-1	no expectations	Magdeburg	0	8
20050615-14:45-0	no expectations	Magdeburg	0	8
20050615-14:45-1	no expectations	Magdeburg	0	8
20050616-08:53-0	no expectations	Magdeburg	0	10
20050616-08:53-1	no expectations	Magdeburg	0	8

*continued on next page*

date	treatment	place	min.bid	participants
20050616-10:17-0	no expectations	Magdeburg	0	8
20050616-10:17-1	no expectations	Magdeburg	0	8
20050616-14:39-0	no expectations	Magdeburg	0	10
20050616-14:39-1	no expectations	Magdeburg	0	10
20050207-10:53-0	expectations w. info	Mannheim	-50	8
20050209-14:09-0	expectations w. info	Mannheim	-50	12
20050209-16:11-0	expectations w. info	Mannheim	-50	6
20050414-10:37-0	expectations w. info	Magdeburg	-50	10
20050414-10:37-1	expectations w. info	Magdeburg	-50	10
20050414-16:35-0	expectations w. info	Magdeburg	-50	10
20050414-16:35-1	expectations w. info	Magdeburg	-50	10
20050415-08:59-0	expectations w. info	Magdeburg	-50	8
20050415-08:59-1	expectations w. info	Magdeburg	-50	8
20050415-11:11-0	expectations w. info	Magdeburg	-50	10
20050415-11:11-1	expectations w. info	Magdeburg	-50	10
20050511-10:51-0	expectations	Magdeburg	-50	10
20050511-10:51-1	expectations	Magdeburg	-50	10
20050511-14:55-0	expectations	Magdeburg	-50	10
20050511-14:55-1	expectations	Magdeburg	-50	10
20050512-09:01-0	expectations	Magdeburg	-50	10
20050512-09:01-1	expectations	Magdeburg	-50	8
20050512-12:59-0	expectations	Magdeburg	-50	8
20050512-12:59-1	expectations	Magdeburg	-50	8

## B Conducting the experiment

Participants were recruited by email and could register for the experiment on the internet.

- At the beginning of the experiment participants drew balls from an urn to determine their allocation to seats in the laboratory.
- Then participants took a simple language test (participants had to find the correct word or form to complete a sentence). Those who failed the language test on at least two items out of ten could not participate (this did not happen very often since participants knew about the language test when they booked the experiment).
- The remaining participants obtained written instructions in German (see section B.1). These instructions vary slightly depending on the treatment. In the following we give a translation of the instructions.
- After answering control questions on the screen (see section B.2) subjects entered the treatment. After completing the treatment they answered a short questionnaire on the screen and were paid in cash. The experiment was

done with z-Tree Version 3 $\alpha$  (the final version is documented in Fischbacher, 2007).

## B.1 Instructions

### General information

You are participating in a scientific experiment that is sponsored by the Deutsche Forschungsgemeinschaft (German Research Foundation). If you read the following instructions carefully then you can—depending on your decision—gain a considerable amount of money. It is, hence, very important that you read the instructions carefully.

The instructions that you have received are only for your private information. **During the experiment no communication is permitted.** Whenever you have questions, please raise your hand. We will then answer your question at your seat. Not following this rule leads to exclusion from the experiment and all payments.

During the experiment we are not talking about Euro, but about ECU (Experimental Currency Unit). Your entire income will first be determined in ECU. The total amount of ECU that you have obtained during the experiment will be converted into Euro at the end and paid to you in **cash**. The conversion rate will be shown on your screen at the beginning of the experiment.

### Information regarding the experiment

Today you are participating in an experiment on auctions. The experiment is divided into separate rounds. We will conduct **12 rounds**. In the following we explain what happens in each round.

In each round you bid for an object that is being auctioned. Together with you another participant is also bidding for the same object. Hence, in each round, there are **two bidders**. In each round you will be allocated randomly to another participant for the auction. **Your co-bidder in the auction changes in every round.** The bidder with the highest bid has obtained the object. If bids are the same the object will be allocated randomly.

For the auctioned object you have a valuation in ECU. This valuation lies between 50 and 100 ECU and is determined randomly in each round. **From this range you will obtain in each round new and random valuations for the object.** The other bidder in the auction also has a valuation for the object. The valuation that the other bidder attributes to the object is determined by the same rules as

your valuation and changes in each round, too. All possible valuations of the other bidder are also in the interval from 50 to 100 from which also your valuations are drawn. All valuations between 50 and 100 are equally probable. Your valuations and those of the other player are determined independently. You will be told your valuation in each round. **You will not know the valuation of the other bidder.**

## Experimental procedure

The experimental procedure is the same in each round and will be described in the following. Each round in the experiment has two stages.

### 1st Stage

In the first stage of the experiment you see the following screen *[[here the instructions show a screen similar to figure 2 or figure 3. Other than the figure the screenshots in the instructions did not provide an example bidding function.]]*

At that stage **you do not know your own valuation for the object in this round.** On the left side<sup>6</sup> of the screen you are asked to enter a bid for **six hypothetical valuations** that you might have for the object. These six hypothetical valuations are 50, 60, 70, 80, 90, and 100 ECU. Your input into this table will be shown in the graph on the left side of the screen when you click on “draw bids”. In the graph the hypothetical valuations are shown on the horizontal axis, the bids are shown on the vertical axis. Your input in the table is shown as six points in the diagram. **Neighbouring points are connected with a line automatically.** These lines determine your bids for all valuations **between** the six valuations for which you have entered a bid.

*[[the following paragraph is only shown in the treatments with expectations: On the right side you are asked to enter **your expectations regarding the bids of the other bidder.** Please enter again for six hypothetical valuations **your expectation of the bid of the other bidder.** If your expectation regarding the bids of the other bidder deviates from the actual bids of the other bidder then an amount which depends on the size of the deviation will be subtracted from your account.]]*

The screen of the other bidder looks identical. He also enters bids for six hypothetical valuations *[[the following only in treatments with expectations: and expectations regarding your bids]]*. You and the other bidder can not see your mutual bids and expectations.

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<sup>6</sup>In the no expectation treatment this was the right side.

## 2nd Stage

The actual auction takes place in the second stage of each round. In each round we will play not only a single auction but **five auctions**. This is done as follows: **Five times a random valuation is determined** that you have for the object. Similarly for the other bidder five random valuations are determined. You see the following screen:

*[[here the instructions show a screen similar to figure 4. Other than these figures the screenshots in the instructions do not provide example bidding functions, bids, valuations, and payoffs.]]*

For each of your five valuations the computer determines your bid according to the graph from stage 1. If a valuation is precisely 50, 60, 70, 80, 90, or 100 then the computer takes the bid that you gave for this valuation. If a valuation is between these points then your bid is determined according to the connecting line. In the same way the bids of the other bidder are determined for his five valuations. Your bid is compared with the one of the other bidder. The bidder with the higher bid has obtained the object.

### Your income from the auction:

For each of the five auctions the following holds:

- The bidder with the higher bid gets the valuation he had for the object in this auction added to his account minus his bid for the object.
- The bidder with the smaller bid gets **no income** from this auction.

*[[[the next two paragraphs and the screenshot are only shown in the treatments with expectations:*

**The possible reduction if expectations are not correct** The following screen again shows the expectations you entered in the first stage:

*[[here the instructions show a screen similar to figure 4 or 5. Other than these figures the screenshots in the instructions do not provide examples for expected bidding functions, no examples for income and no examples for a loss.]]*

The average difference between your expectations and the actual bids of the other bidder for the six hypothetical valuations 50, 60, 70, 80, and 100, multiplied with the conversion factor that is shown on the screen, is subtracted from your account.]]]

**You total income in a round is the sum of the ECU income from those auctions in this round** *[[the following part is only shown in the treatments with expectations: minus the reduction for your incorrect expectations regarding the other bidder.]]*

This ends one round of the experiment and you see in the next round again the input screen from stage 1.

At the end of the experiment your total ECU income from all rounds will be converted into Euro and paid to you in cash together with your Show-Up Fee of 3.00 Euro.

Please raise your hand if you have questions.

## B.2 Control questions

After participants had read the instructions they were asked to answer control questions. These questions were implemented with z-Tree. Questions were presented and answered sequentially. When a question was answered correctly, participants saw the text “This answer is correct” (in German). Otherwise participants saw the text “This answer is not correct”. In this case they got a brief explanation how to derive the correct answer for this question.

The structure of this treatment was (translated into English) as follows:

- The following control questions are supposed to improve your understanding of the experiment. We use some arbitrarily chosen examples to make you familiar with the calculation of profits and other rules in the auction.

Please answer the following questions. You can check yourselves whether your answers are correct. The actual experiment will start after the last question.

- Please note: When you enter numbers with a decimal fraction you have to use the decimal point as a separator, not the decimal comma.
- If you need a calculator, please click on the symbol on your screen.

1. Assume your valuation is 63.25 ECU and your bid that is derived from the bid function in the graph is 40 ECU. What is your income in this auction if
  - (a) the other bidder bids less than your bid?
  - (b) the other bidder bids more than your bid?



2. Assume your valuation is 50 ECU and your bid that is derived from the bid function in the graph is 60 ECU. What is your income in this auction if
  - (a) the other bidder bids less than your bid?
  - (b) the other bidder bids more than your bid?
3. Assume your valuation in this auction is 76.20 ECU. What is your valuation in the next auction?
  - 76.20 ECU / one can not say / 0 ECU
4. Assume your valuation in this auction is 51.67 ECU. What is the valuation of the other bidder in this auction?
  - one can not say / 51.67 ECU / 100 ECU
5. The following table shows an example for your expectations regarding the bids of the other bidder as well as the actual bids of the other bidder.

value	expected bid	actual bid
50	40	40
60	40	40
70	40	30
80	40	40
90	40	50
100	40	50

What amount will be subtracted from your account due to wrong expectations if the conversion factor is 1?

6. Assume that in one round you have won one auction with a valuation of 80 ECU and a bid of 62 ECU. Furthermore, you lost 7 ECU due to wrong expectations. What is your total income from this round?

### B.3 End of the experiment

At the end of the experiment participants completed a questionnaire, again with z-Tree. From their answers we know that about 20% of all participants were female, their median age was 23, about 68% were students of economics and business administration, 73% had participated already in another experiment, and 33% already in another experiment with auctions (Subjects could participate only once in the experiment that we describe in this paper). They found the experiment not very complicated (on a scale from 1 (not complicated) to 5 (very complicated) the average rating was 1.56).

After participants had completed the questionnaire each of them obtained a sealed envelope with their profit from the experiment and left the laboratory.