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# The impact of the irrelevant – Temporary buy-options and bidding behavior in online auctions*

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**Abstract**

In a laboratory experiment, we investigate the impact of temporary buy-options on efficiency, revenues, and bidding behavior in online proxy-auctions when bidders have independent private valuations. We show that the introduction of a buy-option reduces efficiency and at the same time fails to enhance revenues. In particular, we observe that the former presence of a temporary buy-option lowers final prices in an auction (even though the option is no longer available once an auction has started). If bidders have imprecise information about their private value, auction prices are increasing in the price of the buy-option which suggests anchoring as an explanation. Surprisingly, the former presence of a temporary buy-option also tends to reduce final auction prices if bidders are perfectly informed about their private value. In fact, we demonstrate that bidders are reluctant to bid above the option price regardless of the precision of their private information and the price of the option.

*Keywords:* Online Auctions, Experiments, Buy-options
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## 1 Introduction

Online auctions seem to evolve as *the* terms-of-trade in a globalized world. eBay—the most successful Consumer-to-Consumer (C2C) market place—reported for the first quarter of 2006 a net revenue of 1.4 billion US \$. On average the auction houses' web-page enjoys 1.2 billion hits per day leading to 345 million search requests per day (see eBay (2006)). This success is usually attributed to substantially reduced search (or more general transaction) costs compared to more conventional trading mechanisms, and a better matching of demand and

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supply due to the mere size of the platform. While improved matching and reduced transaction costs are expected to force prices of similar products to converge, empirical investigations of online auctions show a surprisingly persistent price dispersion (see *e.g.* Roth and Ockenfels (2002), Lee and Malmendier (2006), or Dodonova and Koroshilov (2004)) even though the trade mechanism is always a proxy auction.[1] The burgeoning (theoretical) literature on auction design offers many explanations why design *details* such as a particular ending rule or a reserve price may well influence the final price of an auction (see *e.g.* Milgrom (2004) for an overview or as an example Ockenfels and Roth (2006) for the case of ending rules).[2] Numerous empirical studies confirm the predictive power of these theoretical models (see *e.g.* Roth and Ockenfels (2002) or Katkar and Reiley (2006)) and demonstrate their usefulness as a guideline for buyers and sellers at (online) auction houses.[3]

Recently, a particular design tool offered by online auctions has attracted a lot of attention: Buy-it-now-options (henceforth, BIN options) provide an opportunity for the seller to announce a price at which s/he is willing to sell the commodity directly.[4] Around one third of all deals at *e.g.,* eBay are fixed price transactions (according to *Wall Street Journal*, 05/25/2006). eBay's annual report (eBay (2006)) indicates that 30 % of gross merchandize sales (roughly 5 billion US $) are purchases through buy-options. Theoretically, the opportunity to trade at a fixed price is inferior for the seller as it avoids competitive bidding. It can, however, also become revenue enhancing, because fixed price transactions avoid waiting time in an auction or offer an insurance against (uncertain) final auction prices—both enhancing the value from a buyer's perspective and/or the revenue of the seller.[5]

A growing empirical literature tries to estimate the revenue-effects of BIN options and thereby to decide which of the theoretical effects dominates. Durham et al. (2004) utilize data from a field experiment with eBay coin auctions to demonstrate that auctions with a BIN option lead to significantly higher revenues than those without. In their dataset, BIN options

[1]In a proxy auction participants are asked to submit their willingness to pay to an automatized bid agent who overbids other bid agents as long as the current price is below the submitted willingness to pay. It is easy to see that this format is equivalent to a second price sealed bid auction.

[2]The traditional literature on auction design focuses on monopolistic auctioneers who maximize their revenue. However, *e.g.,*Peters and Severinov (1997) or Ellison et al. (2003) show that heterogenous auction designs—and revenues—can also be sustained in an equilibrium of a game between competing auctioneers (like *e.g.,* sellers in online auctions) who offer similar commodities.

[3]For an overview of the growing theoretical and empirical literature on online-auctions see Ockenfels et al. (2006).

[4]At most auction sites including eBay and biz.com, the option is no longer available if a potential buyer submitted a bid and (as a consequence) the auction started. These options are typically referred to as *temporary.* Some auction sites like Yahoo or Amazon offer buy-options that remain valid throughout the auction process (referred to as *permanent*). For a theoretical investigation of the different designs see Reynolds and Wooders (2006). Our study focuses on temporary options.

[5]We summarized the most important theoretical results in Appendix A. For a detailed analysis see *e.g.,* Budish and Takeyama (2001), Reynolds and Wooders (2006), and Matthews and Katzman (2006). A comprehensive overview of the various theories and empirical investigations into buy-options can be found in Ockenfels et al. (2006), Section 5.

were used almost exclusively by sellers with a high reputation, and the authors demonstrate that this may well explain the entire price dispersion. Hendricks et al. (2005) analyze data from auctions of a particular Texas Instruments calculator and also find significantly higher revenues for auctions with a BIN option. But as auctions with BIN option also exhibited significantly higher minimum bid requirements, it is impossible to pin down the sole influence of the BIN option.[6] Finally, Dodonova and Koroshilov (2004) use a dataset of bracelet auctions at biz.com to show that final auction prices are increasing in the BIN price (for a given bracelet with identical product descriptions). They suggest that this result is driven by anchoring to (irrelevant) information given by the BIN price—a price that is after all irrelevant in private value auctions once the auction has started.[7] Other studies support the general conclusion that cognitive bounds and biases are rather important to understand real-life market performance. Lee and Malmendier (2006), for instance, investigate board-game auctions at eBay and find that final prices are on average higher if the seller states a higher retail price. They attribute this result to anchoring as well.

All in all, empirical studies hardly manage to isolate the revenue (and efficiency) effect of BIN options. The multitude of confounding factors (such as seller's reputation, other design tools, retail prices *etc.*) and the endogenous choice to participate in an auction imposes restrictions on the analysis of field data. Moreover, while theories on revenue effects of BIN options are nested in a private value framework, auctions of *e.g.,* coins clearly exhibit a strong common value component. According to a recent study by Shahriar and Wooders (2006), BIN options can be hardly revenue enhancing in a common value framework as long as bidders behave rational. However, they demonstrate potential positive revenue effects of the option in a model with boundedly rational bidders who do not correctly anticipate the winner's curse. The multitude of confounding factors and the crucial role of value-generation therefore suggests a laboratory experiment which is able to control for these issues and allows for a better judgement of the explanatory power of standard theory next to models that explicitly encounter cognitive limits.

In this laboratory study, we want to abstract from common (or interdependent) value components and any confounding impact by other design tools or reputational issues and fully concentrate on the behavioral aspects of the introduction (and price) of a BIN option. We endow participants with private valuations that are independently drawn from the same (uniform) distribution. Moreover, participants are assigned to a certain auction. Finally,

[6]A similar conclusion has been reached by Anderson and Singh (2004). In their dataset of Palm Pilot auctions on eBay they observe that high-volume sellers typically use a combination of a BIN option and a *low* minimum bid. Yet again, the effect of the BIN option is hard to disentangle from reputational effects and the impact of other design tools (*i.e.,* the minimum bid) due to the lack of heterogeneity.

[7]Anchoring is a feature of heuristics for decision making under uncertainty that labels the psychological bias to adjust beliefs to new information in an insufficient way, or to use irrelevant information as an anchor for decision making in uncertain environments (see Tversky and Kahneman (1965)).

the only design tool we vary across treatments is the BIN option (*i.e.,* its presence and its price—high or low) such that the respective impact can be isolated. To identify the relevance of anchoring we vary the precision of the participants' information about their private value: For a given BIN price, we conduct a treatment where participants precisely know their private value (*certainty environment*), and another treatment where they only know an interval for the respective private value (*uncertainty environment*).

We find the following set of results. First of all, the higher the option price the less popular the option and the higher efficiency in the certainty environment. In particular, introducing the option unambiguously reduces efficiency. These results do not carry over to the uncertainty environment where the presence and price of an option does not have significant influence on efficiency. Second—and maybe more surprisingly—the introduction of a BIN option unambiguously reduces the seller's revenue, independent of the BIN price or the precision of information about private values. This result can be traced back to the fact that the (former) presence of a BIN option tends to reduce the final price of the auction. Recall that the option is no longer available once an auction started and its price is expected to be completely irrelevant for the bidders as it does not effect their private value (and the weakly dominant strategy to reveal it). Nonetheless, we observe that less bids are submitted above a given BIN price than in a treatment without BIN. This lends support to the hypothesis that anchoring plays a role in our setting.

Recall that in the certainty treatment subjects are informed about their own valuation but remain uninformed about their opponents' valuation. Hence, the BIN price can only serve as an anchor for the values of the *other* subjects or a fictitious auctioneer's willingness to accept. The literature on overbidding in second-price auctions (see *e.g.,* Andreoni et al. (2005) and Cooper and Fang (2006)) and on social preferences (see *e.g.,* Bolton and Ockenfels (2000) and Fehr and Schmidt (1999)) indicates that information about other bidders' values or the seller's willingness to accept indeed displays relevant information and may eventually influence bidding behavior. In fact, we demonstrate that high BIN prices discourage bidding which suggests that bidders indeed take the BIN price as a reference point for the values of other bidders and consider the case of a high BIN price as a "mission impossible". In the uncertainty treatments, however, subjects are also uncertain about their *own* valuation (which is a relevant piece of information even *if* they stick to the weakly dominant strategy to reveal it). Indeed, final auction prices are highest without BIN option followed by the case of a high BIN price and lowest with a low BIN price—in line with the hypothesis that bidders consider the BIN price as a signal for their own valuation.

We regard this study as an indicator for the importance of behavioral aspects in the design of electronic market places. In particular, we demonstrate how the provision of seemingly irrelevant information may well systematically influence bidding behavior in a detrimental way from a seller's or an efficiency point of view.

The remainder of the paper is organized as follows. In Section 2 we present the experimental set-up. Section 3 reviews some testable theoretical results. The analysis of our data is presented in Section 4. Eventually, Section 5 concludes by relating our findings to other studies, identifying the lessons to learn, and evaluating the limits of our work.

## 2 Experimental set-up

We conducted an experiment with a 3×2 between-subjects design as depicted in Table 1. In

| | *Certainty* over private value | *Uncertainty* over private value |
|---|---|---|
| *No BIN* option | *CN* | *UN* |
| *Low BIN* price | *CL* | *UL* |
| *High BIN* price | *CH* | *UH* |

Table 1: *Treatments.*

one dimension we varied the BIN option—either no BIN option at all (*No BIN*), or a BIN option with a low (*Low BIN*) or a high BIN price (*High BIN*). Each of the different BIN option conditions was combined with different degrees of precision of the subjects' private information about the value of the commodity. Subjects either knew their private value (*Certainty*) or they only knew an interval in which the value was placed (*Uncertainty*). In each treatment, subjects played ten auctions in groups of four bidders. We used the partner-matching protocol, *i.e.* each group's composition was the same over all ten rounds. Each auction followed the following steps:

1. *Information about private value.* In the Certainty treatments the subjects were informed about their private value $v$ which was a number chosen from the uniform distribution over the integers in the interval $[65, 135]$. In the Uncertainty treatments subjects were only informed about a lower and upper bound for their private value $v_{\min}$ and $v_{\max}$. Furthermore, subjects knew that $v_{\min}$ was drawn from the uniform distribution over the interval $[50, 120]$ and that the precise value (which was not revealed to the subjects at this stage) was chosen from the uniform distribution over the interval $[v_{\min}, v_{\max}(= v_{\min} + 30)]$.

   To facilitate across-treatment comparisons, we randomly determined the private values of the participants only once, *i.e.* we drew the lower interval boundary and the respective value within the interval for treatment UN and used the same set of intervals and values for the other Uncertainty treatments. For the Certainty treatments we used the midpoints of the drawn intervals as private values.

2. *Decision upon BIN option execution.* For the Low BIN and the High BIN treatments, all subjects were given a common BIN price and asked whether they would like to buy the good for this particular price. Although each subject had to decide upon an application for the option, only the decision of one randomly chosen bidder became decisive. If this subject made use of the BIN option then he bought the good for the BIN price. If this subject declined the BIN offer the auction started.[8]

   In the Low BIN treatments the BIN price was set to the average of the second and third highest value. In the High BIN treatments the BIN price was set to the average of the highest and the second highest value. For the Uncertainty treatments the BIN prices were calculated from the respective expected values in right the same way. If the resulting BIN price was not an integer number, it was rounded down. Our intention was to offer BIN option prices that were sufficiently distinct as to induce different market performance (and potentially bidding behavior). In particular, in the Certainty treatments at most one subject (the bidder with the highest valuation) is expected to apply for the option with the high price, while at most two subjects (the two bidders with the highest valuations) are expected to apply for the option with a low price.[9]

3. *Bidding decisions in the auction.* If no BIN option was available or a subject was selected who did not apply for the option, an English auction with proxy bidding was executed. During the auction subjects could at any time submit proxy bids which were higher than the current price of the auction. At each point in time and for given proxy bids, the current winner was the subject with the highest current proxy bid and the current price was equal to the second highest current proxy bid (proxy bid plus one in those cases where the higher bidder came in later). In case of a tie, precedence was given to the bidder who submitted the bid first. The bidders were continuously informed about whether they are the current winning bidder or not and about the current price. For the treatments with BIN option the forgone BIN price was also displayed. The auction duration was set on 2 minutes in all treatments, but the auction was extended to at least another minute if a new proxy bid was submitted by one of the subjects. Only in case no bid was posted in the last minute, the auction ended. This way subjects always had the opportunity to react on each others bids and incentives to delay bids until the last seconds of the auction (sniping) were eliminated.[10]

4. *Feedback.* At the end of each round (after a BIN execution or the end of an auction),

[8]This procedure mimics that the BIN option is only available as long as nobody started to bid (temporary option). The randomly chosen bidder can be seen as the first to see the good. If he starts to bid he implicitly declines the BIN offer and eliminates it for all other bidders.

[9]Actual individual decisions certainly depend on the individual's preferences as we detail in the next section and in Appendix A.

[10]*I.e.,* we used a soft ending rule as discussed in Roth and Ockenfels (2002).

subjects were informed about the final price of the good, whether they bought it or not, and what their final payoff is going to be. No additional information about the others' values, bids or profits was given.

The experiment was computerized and conducted in the experimental computer laboratory at Maastricht University (Faculty of Economics and Business Administration). The software was programmed within the z-Tree toolbox of Fischbacher (2007). Subjects were invited via email to register for a "market experiment" on a website. In total we had 21 sessions with 60 bidder groups (ten for each treatment) of four bidders. In each session subjects received written instructions (see Appendix B). They could study the instructions at their own pace and ask clarifying questions privately to the instructors. Before the experiment started, every subject had to answer some control questions correctly (see Appendix C). After the experiment, subjects were paid off in cash. The average payoff per subject was about € 15.- with a session lasting between 80 and 110 minutes. In order to avoid losses due to overbidding, subjects started with an initial budget of € 9.

# 3 Testable predictions

To structure the further analysis and to derive some baseline hypotheses, we continue with a brief review of theoretical results on BIN options that are relevant in our setting.[11] In the remainder of the paper we denote by $p^*$ the final price in an auction (the price at which the (fictitious) commodity is sold), and by $p_B$ the BIN price (the price at which the (fictitious) commodity can be bought before the auction starts).

## 3.1 Theoretical benchmark

Suppose that subjects are risk neutral and maximize their monetary payoff. If this is common knowledge, it is a weakly dominant strategy for every subject to submit his private value in the Certainty treatments and the midpoint of the respective interval in the Uncertainty treatments whenever an auction started. In particular, this is independent of the presence and the price of the BIN option, because the option becomes unavailable as soon as the auction starts. Hence, we can formulate a first baseline hypothesis (for a more detailed discussion see Observation 1 in Appendix A).

**Hypothesis 1** *(i) The presence of a BIN option has no impact on $p^*$. (ii) $p^*$ is independent of $p_B$.*

Hence, a subject who decides upon an application for the option chooses between the expected utility from an auction (which depends on $p^*$ but not on $p_B$) and the utility from executing

[11] For a more detailed discussion of the theoretical background see Appendix A or the original contributions by Budish and Takeyama (2001), Matthews and Katzman (2006), or Reynolds and Wooders (2006).

the option (which depends on $p_B$ but not on $p^*$). As a consequence, for a given configuration of private values, BIN applications should increase as $p_B$ decreases. This provides another hypothesis for across treatment comparisons (see also Observation 2 in Appendix A).

**Hypothesis 2** *The lower $p_B$ the more applications for the BIN option.*

With respect to revenues, recall that in the High BIN treatments $p_B$ is between the highest and the second highest value. Hence, any execution of the option leads to a revenue *above* the second highest value (which is the equilibrium price in the auction). In the Low BIN treatments, however, $p_B$ is between second and third highest value and any execution leads to a revenue *below* the second highest value. Whether there are applications to the option, however, depends on the configuration of valuations and individual preferences (as we discuss in more detail in Appendix A). *E.g.,* a subject's application decision depends on his risk attitude or patience.[12] However, some configurations of valuations are such that even a risk neutral and patient subject should apply for the option (because $p_B$ is below the subject's expectation of $p^*$). Hence, we expect to observe applications for the option (and therefore also executions). This leads to the following hypothesis.

**Hypothesis 3** *(i) Revenues in the High BIN treatment are above revenues in the No BIN treatment. (ii) Revenues in the Low BIN treatment are below revenues in the No BIN treatment.*

Finally, we discuss the impact of a BIN option on efficiency. Thereby, we focus on allocation efficiency, that is, we call an allocation efficient if the subject with the highest value (or highest midpoint of the interval in the uncertainty case) receives the (fictitious) commodity.[13] If subjects stick to their weakly dominant strategy, an auction always results in an efficient allocation. More than one bidder applying for the option, however, leads to an inefficient allocation with a strictly positive probability. Now recall again that in the High BIN treatment only the subject with the highest valuation gains from executing the option. Hence, no efficiency loss is to be expected in this case. For the Low BIN treatment, however, more than one BIN application can be expected for some value-configurations. This leads to the next hypothesis (see also Observation 3 in Appendix A).

**Hypothesis 4** *(i) Allocation efficiency in the High BIN treatment does not differ from allocation efficiency in the No BIN treatment. (ii) Allocation efficiency in the Low BIN treatment is smaller than allocation efficiency in the No BIN treatment.*

[12] Budish and Takeyama (2001), Matthews and Katzman (2006), and Reynolds and Wooders (2006) show that a BIN option becomes ceteris paribus more attractive for a subject if he is more risk averse or more impatient.

[13] To allow for comparisons between Certainty and Uncertainty treatments, we abstract from inefficiencies that occur due to the randomization over the interval in the Uncertainty treatments, meaning that if the intervals of two subjects overlap, the subject with the higher midpoint has to win the auction for the allocation to be efficient.

### 3.2 Anchoring

The previous hypotheses are implications of rational behavior. In the following we want to elicit some consequences on behavior if actors are no longer fully rational. One particular important psychological bias discussed in the empirical literature (see Section 1) which could have an effect in our experimental setting is anchoring.

"Anchoring and Adjustment" is a heuristics introduced by Tversky and Kahneman (1965) to describe decision making *under uncertainty*. In an overview article, Chapman and Johnson (2002) define an anchoring procedure as one in which "a salient but uninformative number is presented to subjects before they make a numerical judgement" in such a way that the uninformative number eventually influences the judgement. The authors thereby emphasize the importance of a compatibility between the target information and the anchor. In our case, the BIN price appears as salient but uninformative information for the subsequent bidding decision. Moreover, the BIN price is compatible with the subject's willingness to bid. If subjects stick to the weakly dominant strategy to submit their private value, they possess all relevant information in the Certainty treatments and no anchoring is to be expected in this case. Hence, Hypothesis 1–4 should remain valid.

In the Uncertainty treatments, however, subjects might use the BIN price as an anchor when they determine their willingness to bid (*i.e.,* their private value). In general, this may well lead to lower or higher prices at the end of an auction compared to treatments without the former presence of the option (rejecting Hypothesis 1(i) and Hypothesis 3(i) and (ii)). Moreover, if the BIN price plays the role of an anchor, a subject's willingness to bid is expected to raise in the BIN price. Hence, $p^*$ should be larger for the High BIN than for the Low BIN treatments which would lead to a rejection of Hypothesis 1(ii).

## 4 Results

The experiment generates data of 600 auctions (*i.e.,* 100 different auctions, each conducted for the six different treatments in 10 independent groups). In the following we split the analysis in two major parts. Subsections 4.1, 4.2, and 4.3 will take a helicopter view and analyze efficiency, applications for the BIN option and revenues in total. For statistical tests we aggregate the data over all rounds for each particular group. This results in 60 independent observations (six treatments with 10 observations each). Each group within a given treatment faced different private values and each configuration of values was used once in each treatment. In order to avoid problems with pairwise equivalent stimuli we use the Wilcoxon signed-rank test instead of Mann-Whitney-U.

In Subsections 4.4, 4.5 and 4.6 we focus our analysis on the effect of the presence or absence of a BIN option on the subsequent auction. When aggregating the data to independent observations we therefore took only those rounds into account where an auction resulted in all compared treatments. In all these comparisons we provide the number of auctions the analysis is based on.

### 4.1 Efficiency

Hypothesis 4 suggests that efficiency should not be independent of the presence and price of the option. In fact, the High BIN treatment should not differ significantly from the No BIN treatment with respect to efficiency while the Low BIN should. Table 2 displays two different measures for efficiency (# *eff* and *eff*) and the respective between treatment comparison. # *eff* is the fraction of auctions that yields an efficient outcome. This measure is insensitive to the extent of potential efficiency losses. The second, alternative, measure takes into account to which extent efficiency is violated, and reads $\mathit{eff} = \frac{v(\text{winner})}{v(\text{highest})}$ (the winner's valuation divided by the highest valuation). In particular, $\mathit{eff} = 1$ if the person with the highest value wins, and $\mathit{eff} = 0$ if the winning subject does not value the good at all (in fact, $\frac{65}{135}$ would be lowest value for *eff* that possibly could be observed).

| Compare | avg *eff* | avg # *eff* |
|---|---|---|
| CN – CL | $0.990 >_{.004} 0.944$ | $0.88 >_{.023} 0.65$ |
| CN – CH | $0.990 \sim_{.375} 0.993$ | $0.88 \sim_{.266} 0.94$ |
| CL – CH | $0.944 <_{.004} 0.993$ | $0.65 <_{.004} 0.94$ |
| UN – UL | $0.983 \sim_{1.00} 0.973$ | $0.74 \sim_{.914} 0.74$ |
| UN – UH | $0.983 \sim_{.922} 0.982$ | $0.74 >_{.047} 0.83$ |
| UL – UH | $0.973 \sim_{.492} 0.982$ | $0.74 \sim_{.117} 0.83$ |
| CN – UN | $0.990 \sim_{.232} 0.983$ | $0.88 >_{.008} 0.74$ |
| CL – UL | $0.944 <_{.049} 0.973$ | $0.65 \sim_{.109} 0.74$ |
| CH – UH | $0.993 >_{.064} 0.982$ | $0.94 >_{.055} 0.83$ |

Table 2: *Efficiency. E.g.,* $>_{.004}$ in the first row indicates that the respective efficiency measure is larger for treatment CN than treatment CL at a significance level of 0.004 (significance is based on a Wilcoxon signed-rank test (two-sided) with bidder groups being independent observations).

We find that in the Certainty treatments (top triple of rows) a low BIN price leads to significantly more inefficiency (for both measures) in comparison with no BIN option or with a high BIN price. In contrast, there is no significant difference between efficiency in the High BIN and the No BIN treatments. This is in line with Hypothesis 4.

**Result 1** *(i)* $\mathit{eff}(CN) = \mathit{eff}(CH)$ *cannot be rejected. Significant with respect to both efficiency measures are the following relations: (ii)* $\mathit{eff}(CN) > \mathit{eff}(CL)$*, and (iii)* $\mathit{eff}(CH) > \mathit{eff}(CL)$.[14]

For the Uncertainty treatments (middle triple of rows) only one comparison is found to be significant for one particular measure. No BIN treatments lead to significantly more auctions

[14] If not indicated otherwise all results are significant in a (two-sided) Wilcoxon signed-rank test.

with an efficient allocation (measured by # *eff*) than High BIN treatments. Almost identical values for *eff*, however, indicate that this result is driven by auctions with a small difference between highest and second highest valuation. Hence, the Uncertainty treatments do not lend robust support to any part of Hypothesis 4.

Part of the reason for the incoherence between Hypothesis 4 and the comparisons of Uncertainty treatments can be found in the last three rows which depict the effect of uncertainty on efficiency for a given BIN option (or in its absence). For the No Bin and the High BIN case, uncertainty reduces efficiency (though not significant for the No BIN case measured by *eff*). In contrast, uncertainty seems to increase efficiency in the Low BIN treatments (though not significant according to # *eff*).

To interpret these findings, note that the introduction of uncertainty can affect efficiency in two ways. A more uncertain environment may lead to different BIN application decisions *and* a modified bidding behavior. To evaluate the relative importance of these two aspects, we continue with an analysis of BIN applications.

## 4.2 Applications to execute the BIN option

With respect to the number of BIN option applications, Hypothesis 2 indicates that applications are expected to be less frequent if the price of the option increases. Table 3 confirms this. Note that Table 3 indicates that subjects did not just follow the rule of thumb to apply

| | Certainty | Uncertainty |
|---|---|---|
| No BIN | – | – |
| Low BIN | 165 : 6/26/65/3/0 | 162 : 4/39/48/9/0 |
| High BIN | 62 : 39/60/1/0/0 | 75 : 34/58/7/1/0 |

Table 3: *Statistics of the demand for a BIN option.* In the baseline treatment the demand is 0 by definition. The entries in the other fields read the following: 6/26/65/3/0 means that in 6 cases none demanded the option, in 26 cases 1 subjects out of 4 demanded the option, in 65 cases 2 subjects, in 3 cases 3 subjects and in 0 cases 4 subjects demanded the option. The number before the colon is the total number of BIN applications, i.e. $6 \cdot 0 + 26 \cdot 1 + 65 \cdot 2 + 3 \cdot 3 + 0 \cdot 4 = 165$. Each cell represents 100 auctions with 4 participants and therefore 400 decisions in total.

for the option whenever their private value is above the option price. This would have lead to 200 applications in the Low BIN and 100 applications in the High BIN case.

A comparison between the Certainty and the Uncertainty treatments, however, is more subtle. We observe a larger number of BIN applications and a shift to the right of the respective distribution (more applications by subjects with lower private values) in the Uncertainty treatments for a high BIN price. This is in line with the expectation that a BIN option should become more attractive if the environment gets more uncertain (assuming, for instance, risk averse bidders as detailed in Reynolds and Wooders (2006)). However, this is not observed for low BIN prices. Here, the number of BIN applications decreases slightly and the respective distribution gets more dispersed. To understand this result, observe that it is not a weakly dominant strategy for a risk averse bidder to submit the expected value (the midpoint of the interval) in the Uncertainty treatments. His optimal strategy—and the respective expected payoff from an auction—depends not only on his own degree of risk aversion but also on the respective beliefs about his opponents' preferences.[15] The lower the option price, the more subjects are in general tempted to consider the option. Heterogeneity in the beliefs and preferences would therefore explain the more dispersed distribution. For our purposes it is nonetheless more important to note that the total number of BIN applications in the Low BIN treatments does increase due to the introduction of uncertainty and so does the number of auctions where other subjects than the bidder with the highest value apply. Hence, the difference between the Certainty and Uncertainty treatments with respect to efficiency cannot be explained by a change in BIN application decisions. It rather suggests different bidding behavior.

### 4.3 Revenue

From a seller's perspective, the most important aspect of a BIN option is its impact on revenues (*i.e.,* the price of the option in case of its execution and the final price of the auction otherwise). Theoretical expectations (according to Hypothesis 3) are that revenues in the High BIN treatments are larger than without option, and revenues in the Low BIN treatments are smaller than without option. Table 4 shows, however, that the introduction

| Compare | Average Revenue |
|---|---|
| CN – CL | 109.48 $>_{.004}$ 104.98 |
| CN – CH | 109.48 $>_{.049}$ 108.01 |
| CL – CH | 104.98 $<_{.010}$ 108.01 |
| UN – UL | 113.48 $>_{.004}$ 103.68 |
| UN – UH | 113.48 $>_{.020}$ 109.64 |
| UL – UH | 103.68 $<_{.020}$ 109.64 |

Table 4: *Total Revenues.* *Revenue* = $p_B$ in case of an execution of the option and *Revenue* = $p^*$ otherwise. Average $p_B$ for High BIN treatments was 115.06, and for Low BIN 101.19.

of a BIN option unambiguously reduces revenues (rejecting Hypothesis 3(i)), while revenues decrease in $p_B$ (supporting Hypothesis 3(ii)).

**Result 2** *The following relations are significant: (i) Revenue*$(CN)$ > *Revenue*$(CH)$ > *Revenue*$(CL)$*, and (ii) Revenue*$(UN)$ > *Revenue*$(UH)$ > *Revenue*$(UL)$.

[15] A risk averse bidder, for instance, who beliefs that the other bidders are less risk averse expects to win the auction with a small probability and therefore has incentives to execute the option. In contrast if he believes that other bidders are more risk averse than himself, he expects to win the auction and therefore regards a BIN option less valuable. The empirical relevance of risk aversion in the context of proxy-auctions has been emphasized in Shahriar and Wooders (2006).

The results displayed in Subsection 4.2 suggest that the relatively low revenues in the Low BIN treatments can well be attributed to more BIN executions (and as a consequence prices below the dominant strategy equilibrium of an auction). However, any revenue reduction due to an introduction of a high BIN price cannot be due to BIN executions (unless we frequently observe final prices above the second highest value in the No BIN treatments, which is not the case). Whenever the option gets executed in the High BIN treatments, it will yield *higher* revenues than in the weakly dominant strategy equilibrium of the auction. Hence, we have another indicator that the (former) presence of an option affects bidding behavior in the subsequent auction. In the next subsection we further investigate how bidding behavior (and in particular the final price of the auction) is affected by the (former) presence of a BIN option.

### 4.4 Final auction prices

While benchmark theory (see Hypothesis 1) predicts that final prices of the auction are independent of presence and price of the option, we argued in Subsection 3.2 that the BIN price may well serve as an anchor for a subject's willingness to bid in the Uncertainty treatments while we do not expect such an effect in the Certainty treatments. Accordingly, we expect final prices in the Uncertainty treatments to increase in $p_B$ while no difference should be observed in the Certainty treatments. Table 5 depicts the respective results. As motivated in the beginning of the section we only used those rounds for the aggregation to independent observations, where the BIN option was not executed. To control for outlayer-driven results we aggregated the rounds in two different ways: mean and median. The results turn out to be rather robust.

| Compare | # auctions | Average price $p^*$ aggregation via mean | Average price $p^*$ aggregation via median |
|---|---|---|---|
| CN – CL | 51/100 | 112.18 $\sim_{.287}$ 111.06 | 113.10 $\sim_{.285}$ 112.25 |
| CN – CH | 84/100 | 110.12 $>_{.014}$ 107.18 | 111.55 $>_{.029}$ 107.15 |
| CL – CH | 45/100 | 111.91 $>_{.002}$ 108.87 | 112.65 $>_{.018}$ 109.10 |
| UN – UL | 62/100 | 112.68 $>_{.014}$ 105.55 | 114.05 $>_{.012}$ 106.30 |
| UN – UH | 81/100 | 113.52 $>_{.010}$ 108.69 | 116.70 $>_{.012}$ 110.30 |
| UL – UH | 47/100 | 106.02 $\sim_{.131}$ 109.36 | 106.60 $\sim_{.264}$ 110.55 |

Table 5: *Average auction prices $p^*$.* The first column depicts the treatments to compare. The second column provides the number of auctions the comparison is based on. The third and fourth column display the between-treatment comparison of average auction prices when aggregation takes place via the mean respectively the median.

**Result 3** *The following relations are significant based on average and median (i) $p^*(CN) > p^*(CH)$, (ii) $p^*(CL) > p^*(CH)$, (iii) $p^*(UN) > p^*(UL)$, and (iv) $p^*(UN) > p^*(UH)$. (v) $p^*(UH) > p^*(UL)$ is significant on the ten percent level for a one-sided Wilcoxon signed-rank test.*

All in all the data clearly rejects Hypothesis 1(i) (no price change due to the introduction of a BIN option). Only the introduction of a low BIN price for the Certainty treatment does not significantly push down the price.

Also Hypothesis 1(ii) (dependence on $p_B$) can be rejected. However, the dependency of $p^*$ on $p_B$ is not as simple as suggested in Section 3.2. Data for the Uncertainty treatments is in line with the expectation that final prices ($p^*$) increase in the BIN price ($p_B$) (see Result 3(v)). Certainty treatments, however, reject such a relationship and demonstrate that final prices decrease in the price of the option (see Result 3(ii)). Hence, while Uncertainty treatments lend support to the hypothesis that $p_B$ serves as an anchor for a subject's willingness to pay, Certainty treatments show that the actual impact of $p_B$ is more subtle. As subjects' know their private value in the Certainty treatments, a dependence of $p^*$ on $p_B$ suggests that they do not only care for their own valuation in their bidding decisions—also taking information *e.g.,* about their opponents' values or the willingness to accept of a fictitious seller into account—and that $p_B$ serves as an anchor for this kind of information. In the following subsections we try to further pin down the way $p_B$ influences subjects' bidding decision.

### 4.5 Final bid submission

We already saw in Subsection 4.4 that the former presence of a BIN option tends to reduce the final price of the auction. To investigate this on the individual level, we depict in Table 6 the number of bids that are above the respective BIN price.

| Compare | # auctions | # of final bids above BIN price |
|---|---|---|
| CN – CL | 51/100 | $108 >_{.016} 95$ |
| CN – CH | 84/100 | $47 >_{.023} 30$ |
| UN – UL | 62/100 | $144 >_{.004} 97$ |
| UN – UH | 81/100 | $94 >_{.019} 63$ |

Table 6: *Statistics over number of bids above the BIN price.* The first column depicts the treatments to compare. The second column provides the number of auctions the comparison is based on. The third column indicates the number of bids above the respective BIN price and the corresponding significance value for a Wilcoxon signed-rank test.

**Result 4** *Final bids above the BIN price are significantly less often submitted, if the option was available.*

Hence, some individuals seem reluctant to bid more than they would have paid by executing the option. This further illustrates the impact of presence and price of a BIN option on bidding behavior. One possible explanation could be that subjects perceive the BIN price as the valuation of a (fictitious) seller. They might be reluctant to bid above $p_B$ because they do not want to "overpay" him (an argument that could be backed up by theories of social preferences such as inequity aversion).

Another explanation for the observed behavior would be regret by subjects who did not apply for the option (and were decisive), and are therefore reluctant to bid more than $p_B$ throughout the auction because they did not use a cheaper option beforehand. We conducted several regressions of bids on such "regret-histories", but did not find any support for this explanation. Another possible explanation of observed behavior is that bidders take $p_B$ as a signal about the other bidders' private values. This potential explanation is further investigated in the next subsection.

### 4.6 An anchor for what?

The fact that final auction prices are not independent of $p_B$ in the Certainty treatment suggests that subjects take more information into account than just their own private value when forming their bidding decision. We know from recent studies on overbidding in second price auctions that information about other subjects' values indeed influences bidding decision. Andreoni et al. (2005) and Cooper and Fang (2006) show that subjects tend to bid more fiercely if their own value is close to the value of another subject. The authors attribute this pattern to spiteful behavior (subjects want to raise the price another subject with a value just above his own has to pay in the end) or the "joy-of-bidding" (subjects regard winning an auction against a strong opponent as more valuable). Furthermore, subjects can use information about their opponents' values for an estimation of their own winning probability and decide whether bidding is worthwhile in the first place.[16]

To further distinguish between the different possible impacts of information on other subjects' valuation and the respective anchoring function of $p_B$, we compare the final bids of the second highest value holders for the Low BIN and the High BIN treatments.[17] If bidders indeed take $p_B$ as an anchor for the other subjects' values, spiteful behavior or "joy-of-winning" would lead to higher bids for a high BIN than for a low BIN price. If, in contrast, bidders take $p_B$ as an anchor for the probability to win the auction, a higher BIN price may well lead to earlier drop-outs and lower final bids.

An examination of the data using the Wilcoxon signed-rank test (two-sided) on the basis

[16] In fact, subjects almost never follow the dominant strategy to reveal their value to the bid agent and rather overbid each other incrementally like in an English auction. For this bidding pattern, information about private values of opponents may also influence the point in time where bidders drop out and stop bidding because they declare an auction a "mission impossible".

[17] We restrict our comparison to the final bids of the second highest value holders because third and fourth highest value holders often faced current auction prices which they could not overbid anymore. Consequentially it was only the second value holders who had a strong interest to bid up to his willingness-to-pay.

of independent observations lends support for the latter hypothesis. While the final bids of the second value holders in the Low BIN treatment are not significantly different from their values ($p = .375$), the second value holders in the High BIN treatment systematically underbid ($p = .002$) by 2.09 ECU on average. Moreover their final bids are significantly lower in the High BIN than in the Low BIN treatment ($p = .010$).

## 5 Concluding remarks

In this study, we investigated the impact of BIN options on efficiency, revenues, and bidding behavior in a private value proxy-auction. In line with models of rational, payoff maximizing agents, we find that the introduction of a BIN option tends to reduce allocation efficiency. In contrast to these models, however, we show that BIN options unambiguously reduce the seller's revenue. In particular, the introduction of a temporary BIN option tends to reduce the final price of a subsequent auction and bids above the BIN price are less often submitted compared to a control-treatment without option. We discuss how this influence of BIN prices on bidding behavior can be interpreted as anchoring. For an uncertain environment where subjects are only informed about an interval for their private values, the BIN price can be interpreted as an anchor for subject's actual value. Accordingly, the introduction of an option matters and final bids tend to increase in the BIN price. For a certainty environment where subjects are perfectly informed about their private value, final bids are still reduced by the introduction of the option but decrease in its price. Our data suggests that bidders are discouraged by high BIN prices in the sense that bidders with the second highest value no longer bid up to their value but significantly underbid.

Empirical studies such as Dodonova and Koroshilov (2004) or Lee and Malmendier (2006) suggest that sellers (*e.g.,* in online auctions) may sometimes benefit from cognitive shortcomings of the respective buyers. Then, an obvious conclusion is to take these cognitive limits into account when designing the (seller-optimal) mechanism. If, for instance, bidders take the BIN price as an anchor, a sophisticated seller is tempted to set the anchor in such a way that it enhances his revenue. In fact, it is exactly such a strategy that a seller might choose on the basis of the afore-mentioned empirical studies. However, our experiment suggests that this kind of "behavioral mechanism design" is anything but straightforward. Our study demonstrates that a BIN option is not unlikely to *reduce* seller revenues. Hence, we demonstrate the existence of "cognitive costs" that are not necessarily compensated by the revenue-enhancing effects of a BIN option as identified in the theoretical literature (and corroborated by field studies such as Anderson and Singh (2004) or Hendricks et al. (2005) and laboratory experiments such as Shahriar and Wooders (2006)). Our research suggests to be aware of cognitive shortcomings (such as *e.g.,* anchoring effects) and highlights the complex impact of (irrelevant) information in simple bidding processes. From a practical point of view, our experiment supports the design choice at *e.g.,* eBay to not display the BIN price after it expired and questions its ongoing exposition in the (former) design at biz.com.

An interesting research question is of course in how far sellers actually learn to use the BIN option. An appealing framework to answer this question has recently been proposed by Grebe et al. (2006) who invite experienced eBay users to participate in laboratory experiments.

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# A Theoretical predictions

In the following we summarize the key findings of theoretical investigations into BIN options[18] that apply to our experimental set-up. We assume throughout this appendix that subjects are rational and maximize their monetary payoff (and that this is common knowledge). The buyer's decision whether or not to select the BIN option is a choice between two lotteries (see Figure 1): $\mathcal{L}_{\mathrm{y}}$ (application for the option) and $\mathcal{L}_{\mathrm{n}}$ (no application for the option). An optimal decision depends on which of the two lotteries induces the highest expected utility.

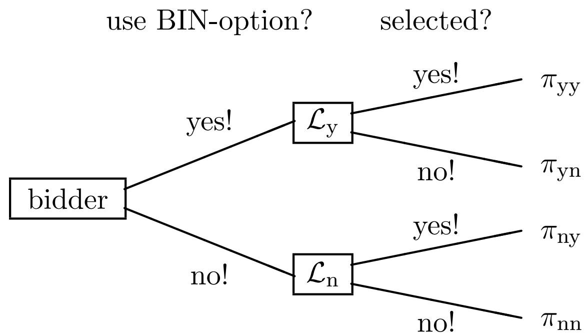


Figure 1: The BIN decision is a choice between lotteries.

In both lotteries the state with the reference bidder being decisive occurs with probability one divided by the number of bidders. With the remaining probability mass the reference bidder is not selected to be decisive in both lotteries. If he is not decisive, his continuation payoff depends on the BIN application decisions of the other bidders and bidding behavior in the auction. As subjects decide upon BIN applications simultaneously, the former cannot be influenced by the reference bidder's application decision. Moreover, private values imply that also bidding behavior should be independent of the BIN application decisions. Hence, we get $\pi_{\mathrm{yn}} = \pi_{\mathrm{nn}}$ and an optimal BIN decision for an expected utility maximizing individual depends on which of the two other continuation payoffs, $\pi_{\mathrm{yy}}$ or $\pi_{\mathrm{ny}}$, is higher. For further reference, we summarize as follows.[19]

**Observation 1** *(i) $p^*$ is independent of $p_B$. (ii) A subject applies for the BIN option if and only if $\pi_{\mathrm{yy}} > \pi_{\mathrm{ny}}$.*

[18]See Budish and Takeyama (2001), Matthews and Katzman (2006), and Reynolds and Wooders (2006). In fact, Matthews and Katzman (2006) emphasize the role of "patience" for the economic performance of BIN options. We abstain from a more detailed discussion of subjects with a certain degree of impatience as the time-frame of our experiment seems to be unfitting for such considerations.

[19]Recall that we denote final prices of an auction by $p^*$ and the price of the BIN option by $p_B$.

## A.1 BIN applications

In the remainder of this appendix, we assume that there are $n$ risk neutral bidders[20] with private valuations that are identically and independently distributed via a differentiable cumulative distribution function $F$ with support on the closed unit interval.[21] Moreover all bidders know the BIN price $p_B$. Because of risk neutrality we can restrict analysis to the Certainty treatment. Results for the Uncertainty treatment are made by considering the midpoint of the respective interval.

For the reference bidder with private value $v$ the continuation payoff $\pi_{\text{yy}}$ is equal to $v - p_B$. The continuation payoff $\pi_{\text{ny}}$ is equal to the payoff of a standard auction and reads

$$\pi_{\text{ny}}(v) = vF^{n-1}(v) - (n-1)\int_0^v v' f(v') F^{n-2}(v')\,\mathrm{d}v'.$$

For the bidder it is optimal to execute the BIN option if and only if the continuation payoff $\pi_{\text{yy}}$ exceeds the continuation payoff $\pi_{\text{ny}}(v) = v - p_B$.

For the situation with four bidders ($n = 4$) with private valuations chosen from the support $[0, 1]$ according to a uniform distribution ($F \sim \text{Un}$), the continuation payoff $\pi_{\text{ny}}$ simplifies to $\frac{1}{4}v^4$. Next we find that each bidder should execute the BIN option if and only if $v - p_B \geq \frac{1}{4}v^4$.

Let $\bar{v}(p_B)$ denote the critical value above which the BIN option should be chosen. Clearly $\bar{v}(p_B)$ is a solution to the equation $v - p_B = \frac{1}{4}v^4$. The only real-valued solution on $[0, 1]$ is displayed in Figure 2.

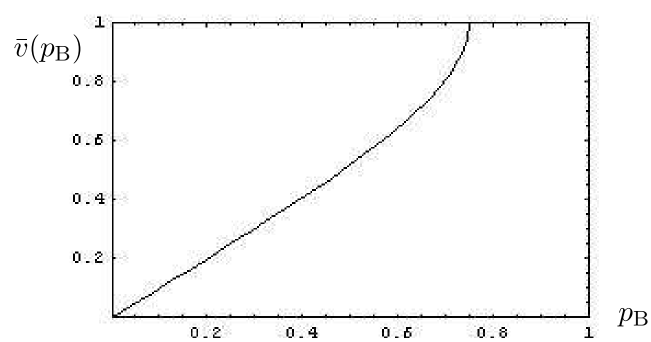


Figure 2: Optimal BIN application

Hence, in expectation the following result holds.[22]

**Observation 2** *The lower $p_B$ the more applications for the BIN option.*

[20] In fact, we assume common knowledge of risk neutrality.

[21] Note that in the experiment the set of possible private valuations was restricted to integers and, hence, discrete. We have chosen the more familiar set-up in this section for expositional ease. All observations are nonetheless robust to such modifications of the model.

[22] Monotonicity statements in Observation 2 and 3 are certainly statements on weak monotonicity.

### A.2 Efficiency

In this paper, we focus on allocation efficiency (*i.e.,* if the subject who values the (fictitious) commodity most actually receives it). For the Uncertainty treatments we call an allocation efficient if the buyer with the highest midpoint of the respective valuation interval receives the commodity. If subjects stick to the weakly dominant strategy to reveal their (expected) valuation, the only source of inefficiency in the Certainty treatment is the execution of a BIN option by a subject that does not hold the highest valuation of all participants. Hence, Observation 2 indicates that

**Observation 3** *(i) The introduction of a BIN option reduces allocation efficiency. (ii) The lower $p_B$ the lower allocation efficiency.*

For the uncertainty treatment, Observation 2-3, depend on (common knowledge of) risk neutrality. The experiment of Shahriar and Wooders (2006) gives an indication that risk-aversion may matter in our experiment. It follows from Reynolds and Wooders (2006) that all observations still hold if subjects have identical attitudes towards risk. If subjects differ with respect to their degree of risk aversion (and their beliefs about other subjects' degree of risk aversion) a bidder with a lower private value can *e.g.,* outbid a more risk averse bidder with a higher private value. This makes a subject's bidding behavior and expected payoff from an auction dependent on its own degree of risk aversion and its beliefs upon other subjects' degree of risk aversion. Such effects can thus be expected to have an impact on allocation efficiency, final prices in an auction (and thereby a subject's expected payoff from an auction), and BIN option executions.

## B Instructions

Dear participant,

thank you for taking part in this experiment!

It will last about 1.5 hours. You will be compensated according to your performance. In order to ensure that the experiment takes place in an optimal setting, we would like to ask you to follow the general rules during the whole experiment:

- Do not communicate with your fellow students!
- Please, switch off your mobile phone!
- Please read the instructions carefully! It is important that you understand the rules of the experiment. If something is not explained well, please raise your hand. We will answer your question privately. The instructions are identical for all participants.

- You may make notes on this instruction sheet if you wish.
- After the experiment please remain seated till you are paid off.
- If you do not obey the rules, the data becomes useless for us. Therefore we will have to exclude you from this experiment and you will not receive any compensation.

Your decisions are anonymous. Neither your fellow students nor anybody else will ever learn them from us.

**General set-up** At the beginning of the experiment, participants are randomly matched into groups of four bidders. The experiment consists of 10 rounds (auctions). In each round a fictitious commodity is auctioned off. If you win the auction you do not receive the commodity but you receive an amount of money equal to your private value $v$ (expressed in Experimental Currency Units (ECU)). In return you have to pay the price ($p$) resulting from the auction (see below). I.e. you make a profit of $v - p$.

The private value ...

[Certainty treatment] or [Uncertainty treatment]

Who wins the auction and what price the winner has to pay is determined in the following way:

[With BIN] or [Without BIN]

... all participants can submit their own bids. The auction works with *proxy-bidding*. Participants submit the maximum they are willing to bid (their *proxy bid*) to a bidding agent who acts as follows. Suppose your bid is equal to $b$. If this bid is below the current price of the auction ($p$), nothing happens. If it is above the current price, the bidding agent submits a bid just above the current price (i.e. $p + 1$). If no one else has submitted a bid above $p + 1$ and no one else submits a higher bid subsequently, the respective bidder will be the winner of the auction and will pay $p + 1$ (making a profit of $v - p - 1$).

If someone else has submitted a bid above $p + 1$, his bidding agent submits $p + 2$. If your bid is also higher than $p + 2$ your own bidding agent submits $p + 3$ and so on. Stated differently, your bidding agent overbids any competing bidding agent as long as the bid does not exceed the willingness to pay that you have submitted to your agent.

Bid submission is costless and every participant can submit as many bids as he likes. However, the bidding agent only recognizes an increase in the willingness to bid (i.e. it is not possible to reduce the maximum bid throughout the auction). Furthermore, he ignores bids below 1 and above 200.

**Displayed Information** Bidders are informed . . .

[Certainty treatment] or [Uncertainty treatment]

. . . Furthermore, the current price (i.e the price that would have to be paid by the participant who has submitted the highest bid if nothing else happens until the end of the auction) is displayed on the screen. Furthermore, each bidder is informed wether he or someone else has submitted the current highest bid.

**End of the Auction** The auction ends after 2 minutes if there are no bid submissions in the last 60 seconds. Otherwise, the auction will be extended to a minute. The auction only ends if there are no incoming bids for at least 60 seconds. At the end of the auction, the winning bidder is selected, the commodity is allocated to him, and he has to pay the final price of the auction.

ECU's are transformed into Euros according to the following conversion rate: $1Euro = 5ECU$. You will obtain an initial endowment of 9 Euro. **If you make losses in an auction these will be deducted from your previous gains (or from your initial endowment). Note that if the losses exceed previous gains and your initial endowment, we will ask you to pay the difference.** You will receive your final profit in cash at the end of the experiment.

After the experiment, we would like to ask you to complete a short questionnaire.

Thank you again and good luck with the experiment!

## [Certainty treatment]

. . . will be determined randomly and independently for every bidder. It will be drawn from the interval between 65 and 135. Each value (including 65 and 135) is equally likely. Before the auction starts, your private value $v$ will be shown to you.

. . . about their private value $v$.

## [Uncertainty treatment]

. . . will be determined randomly and independent for every bidder as follows. First, the computer draws a random number between 50 and 120 (we will refer to this number as $v_{\text{min}}$ from now on). Each number between 50 and 120 is equally likely. $v_{min}$ is a lower bound for your private value. Afterwards the computer draws a number between 0 and 30 (we will refer to this number as $x$ from now on). Again each number between 0 and 30 is equally likely. Your private value $v$ is now determined by $v = v_{\min} + x$. Stated differently, your private value is in the interval $[v_{\min}, v_{\min} + 30]$ and each value between $v_{\min}$ and $v_{\min} + 30 = v_{max}$ is equally likely.

Before the auction starts, $v_{\min}$ and $v_{\max}$ (but not $x$ or $v$) will be shown to you. Hence, you will only know an interval in which your private value $v$ lies.

... about the interval for their private value (i.e. $v_{\min}$ and $v_{\max}$).

### [With BIN]

**Step 1 (Buy it now?)** At the beginning of every session you have to decide wether you want to make use of the "buy-it-now" function (i.e. to buy the commodity at a fixed price $p_B$). The respective decisions of all the participants are collected and the computer randomly selects one participant. The decision of this participant will determine the further events.

If the selected participant has decided to use the "buy-it-now" function, he receives the commodity (i.e. a payoff equal to his private valuation ($v$)) and has to pay the "buy-it-now"-price $p_B$. In that event, the selected participant's profit is $v - p_B$ and the other participant's profits are zero. If the selected participant has decided not to use the "buy-it-now" function, the auction starts.

**Step 2 (Auction)** If an auction starts, ...

### [Without BIN]

After the auction starts, ...

## C Control questions

Please give the answers to the following questions. Then raise your arm. One of the experimenters will come to your place and check whether everything is correct.

1.) [Certainty treatment] or [Uncertainty treatment]

2.) Assume somebody else currently submitted the highest proxy bid of 110. Assume further you observe a current price of 95. You submit a proxy bid of 103. What happens?

__ The price goes up to 103. The other person remains the highest proxy bidder.

__ The price moves to 103. You become the highest proxy bidder.

__ The price stays at 95 because you could not exceed the others proxy bid.

__ The price goes up to 110. The other person remains the highest proxy bidder.

3.) Assume 4 participants A, B, C, D. Each participant submits a proxy bid and does not change this proxy bid anymore. First A submits 56, then B submits 123, then C submits 89, eventually D submits 102. Who buys the object?

__ A __ B __ C __ D

4.) What price does the buyer have to pay?

__ 123 __ 102 __ 56 __ 180

5.) Assume you buy the commodity for a price of 114. Your private value for the commodity is 119. What is the profit you make?

______________________________

6.) Assume you buy the commodity for a price of 117. Your value for the commodity is 99. What is the profit you make?

______________________________

**[Certainty treatment]**

Assume you have a private value of 78 for the commodity. What can you conclude about the values of the other participants in your auction?

__ Their value is also 78.

__ Their value can be 78 but can also be different.

__ Their value must be different from 78.

**[Uncertainty treatment]**

a.) Assume you have a value between 78 and 108 for the commodity. What can you conclude about the values of the other participants in your auction?

__ Their value is also between 78 and 108.

__ Their value might be between 78 and 108 or might not fall into that interval.

__ Their value must be either below 78 or above 108.

b.) Suppose you have a value between 72 and 102.

__ The probability to have a value of 75 is larger than to have a value of 86.

__ The probability to have a value of 75 is smaller than to have a value of 86.

__ The probability to have a value of 75 equals the probability to have a value of 86.