Winner's Curse Without Overbidding

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ABSTRACT

We report a series of second-price auction experiments in which bidders' signals are the sum of a normally distributed value and a normally distributed error. We consider two parallel treatments, one in which values are independent across bidders (the private value treatment) and one in which all values are the same (the common value treatment). Since winning is informative only with a common value, our design allows for a direct test of the "winner's curse." In both treatments, bidders may also fall prey to a "news curse" when they do not sufficiently recognize that high (low) signals make positive (negative) errors more likely. We determine the importance of the two curses using both inexperienced and experienced subjects. Our design also allows us to discriminate between explanations based on loss or risk aversion or a "joy of winning." We find that observed bids in the common value treatment are surprisingly close to the risk-neutral Nash predictions and there seems to be almost no winner's curse. This conclusion is flawed, however, as observed bids in the private and common value treatments are virtually identical. Rather, the effects of the winner's curse are mitigated by a (partial) news curse and some loss or risk aversion. Our results provide a possible explanation for why empirical studies typically find less evidence of the winner's curse than previous experiments, which precluded the occurrence of a news curse.

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1. Introduction

Bidders in an auction often possess less than perfect information about the value of the object for sale. In recent spectrum auctions, for instance, substantial uncertainty existed about the value of the licenses due to the unpredictable demand for future telecommunication services. Alternatively, when companies compete for oil drilling rights, the dispersion in observed bids partly reflects their different assessments of the amount of oil. Both these examples are best modeled as common value auctions since the object's true value is, to a first approximation, the same for all bidders. Bidders' information may differ, however, and in equilibrium the most optimistic bidder wins. When this adverse selection effect is ignored bidders may forgo some profits or even incur a loss: the "winner's curse."

The empirical evidence for overbidding in common value auctions is not clear-cut. For example, some researchers claim that data from auctions for oil leases in the Gulf of Mexico suggest that winning bidders earn less than the market rate of return on their investments given the risks they face. They attribute the lack of high-risk premiums to overly aggressive bidding in the auction. Others, however, refute this explanation and argue that oil companies with access to perfect capital markets should not be expected to earn high-risk premiums.[1]

In contrast, controlled laboratory experiments have provided compelling evidence for overbidding in common value auctions and several models have been put forward to describe this finding.[2] One common explanation is that subjects fall prey to the winner's curse, but alternative hypotheses exist. Lind and Plott (1991, p.344), for instance, conjecture that the observed overbidding in first-price common value auction experiments may be partly due to risk aversion "if its effect is to raise the bidding function as it does in private value auctions." Risk aversion, however, predicts a *downward* shift in bids in second-price common value auctions, which contradicts the persistent overbidding observed in experiments based on this format (Kagel, Levin, and Harstad, 1995). Likewise, Holt and Sherman (2000) report overbidding in a simple two-bidder first-price common value auction where risk aversion has no effect, and interpret this result as evidence for a winner's curse. Neither of these experimental findings, however,

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[1] For (a discussion of) field studies, see, for example, Capen, Clapp, and Campbell (1971), Roll (1986), McAfee and McMillan (1987), Thaler (1988), Ashenfelter and Genesove (1992) and Kagel (1995).

[2] For experimental studies, see e.g. Bazerman and Samuelson (1983), Kagel and Levin (1986), Lind and Plott (1991) and Cox, Smith, Dinkin, and Swarthout (2000). Kagel (1995) provides a comprehensive overview of this literature.

precludes alternative explanations for the observed overbidding, for instance when bidders experience a "joy of winning."

One contribution of this paper is that we provide a more direct test of the winner's curse hypothesis. Our experimental design involves a private and a common value treatment with very similar structures. In both treatments, each bidder receives a signal that is the sum of her value and an (individual-specific) error term. The only difference is that in the private value treatment bidders' values are independent, while in the common value treatment all values are the same.[3] In other words, winning is informative in one of the treatments only. Our design makes the following test possible: if bidders fall prey to the winner's curse, observed bids should be the same in the private and common value treatments *irrespective of bidders' risk attitudes or other confounding factors*.

Our private value treatment differs from the standard setup where bidders know their own value for sure. The absence of value uncertainty seems unrealistic in many real-world auctions, where bidders have no experience with the commodity for sale. For example, a young couple competing for a house may worry whether it will still suit their demands when the composition of their household changes. Even if bidders have gained experience from previous auctions involving similar products, some residual uncertainty is likely to remain. In procurement auctions, for instance, an experienced bidder may have only a rough estimate of the private cost to complete a new project. To conclude, the theoretically convenient assumption of no value uncertainty is best seen as a limit case.

The value uncertainty present in our experiment opens up the possibility of a "base rate fallacy" when prior information is not adequately taken into account.[4] The base rate fallacy implies that bidders do not sufficiently recognize that high (low) signals make positive (negative)

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[3] Subjects in our experiment participate in either a private value or a common value auction. In contrast, Goeree and Offerman (2002) report experimental results for auctions where the object for sale possesses both private and common value elements. In this case, a fully efficient outcome cannot be expected, even in a Nash equilibrium. The intuition is that a bidder with a high private value but a pessimistic signal about the common value may be outbid by a bidder with a worse private value but an optimistic signal about the common value. Goeree and Offerman (2002) find that the comparative statics predictions of the Nash equilibrium are corroborated by the data: efficiency increases when there is less uncertainty about the common value and when more bidders enter the auction.

[4] This possibility is sometimes referred to as "recency." For evidence on the base rate fallacy see, for example, Tversky and Kahneman, 1982; Grether, 1980; El-Gamal and Grether, 1995; see Camerer, 1995, pp. 597-601 for a survey.

errors more likely. As a result, they do not correct for an optimistic (pessimistic) estimate and bid too high (low). Hence, in an auction the base rate fallacy may result in a "news curse" just as neglecting the information conveyed in winning may lead to a winner's curse. While the winner's curse is unique to common value auctions, the news curse can occur both in private and common value auctions.

The news curse can be illustrated as follows. Suppose private values and errors are normally distributed (as in the experiment). When a signal is above average a rational bidder will realize that such "good news" can be attributed to a higher than average value but also to a positive error. A rational bidder will therefore estimate the true value to be somewhere between the average value and her signal. In contrast, a naive bidder with a (complete) base rate fallacy neglects the prior information and takes her signal as the best estimate of the value. As a result, she may pay too much and forgo some profits or even incur a loss: the news curse. To summarize, when information is taken at face value, the winning bidder, who has a high signal on average, may be surprised *ex post* when the object turns out to be worth less than expected (a "good news" curse). Similarly, low-signal bidders may unnecessarily reduce their chance of winning and forgo profits as a result (a "bad news" curse).

There is a vast body of literature on the winner's curse, but none of these papers address the possibility of a news curse. One reason is that previous experiments mostly involved uniformly distributed signals, in which case the object's expected value conditional on a signal equals the signal (except for some "borderline" cases).[5] Hence, by experimental design, a news curse could not occur in these experiments. In many real life situations, however, the distribution of values is probably better approximated by a normal distribution, in which case a news curse can exist. Another contribution is that we determine the magnitudes of the winner's and news curses when values and errors are normally distributed.

We find that observed bids in the common value treatment are surprisingly close to the risk neutral common value Nash predictions, i.e. there seems to be almost no winner's curse. This conclusion is flawed, however, since observed bids in the private and common value

[5] There are private value auction experiments that use non-uniform value distributions (Palfrey, 1985; Chen and Plott, 1998; Kwasnica, 2000). There is no value uncertainty in these experiments, however, so a news curse cannot occur.

treatments are virtually identical. Rather, the effects of the winner's curse are mitigated by a (partial) news curse and some loss or risk aversion. Our results provide a possible explanation for why empirical studies typically find less evidence of a winner's curse compared to previous experiments, which employed uniformly distributed signals (thus precluding the occurrence of a news curse).

A final contribution of our paper is that we are able to distinguish whether loss/risk aversion or a joy of winning causes observed bids to differ from risk-neutral Nash predictions. In previous first-price private value auctions, an upward bias in observed bids is usually attributed to risk aversion. However, overbidding also occurs when bidders derive non-monetary benefits from winning the auction.[6] In our second-price private value auction with value uncertainty, loss/risk aversion predicts a (parallel) downward shift of the bidding function while a joy of winning leads to a (parallel) upward shift. Thus, our design enables us to clearly discriminate between the two hypotheses: the data favor the loss/risk aversion explanation.[7]

The paper is organized as follows. In section 2 we characterize the Nash equilibria and derive the effects of the winner's and news curses. Section 3 discusses the experimental design and section 4 presents the experimental results and data analyses. Section 5 concludes. The Appendices contain data, instructions, and a proof.

2. Design of the Auctions and Theoretical Background

The experiment involves second-price auctions in which the highest bidder wins and pays the second-highest bid. In the common value treatment, bidder i's signal, S_i, is the sum of the *common* value, V, and an individual-specific error term, ε_i:

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[6] Kagel and Levin (1993) conducted experiments based on the third-price private value auction, where risk aversion lowers bids relative to the risk neutral Nash prediction. The evidence they report is mixed: bids are below Nash predictions with five bidders but above Nash predictions with ten bidders. Cason (1995) reports experimental results for the "U.S. Environmental Protection Agency" auction, where the highest bidder wins the object at a randomly drawn price only if the high bid exceeds that price. Cason finds that observed bids exceed the risk-neutral Nash predictions, whereas risk aversion predicts a downward bias. See also Barut, Kovenock, and Noussair (1999) who survey experimental results for all-pay auctions where overbidding is quite prevalent (and may or may not be consistent with risk aversion).

[7] Our design cannot distinguish between loss aversion and risk aversion, since both affect optimal bids in the same manner in second-price private value auctions with value uncertainty (see section 4.3).

$$S_i = V + \epsilon_i, \qquad i = 1, \ldots, n. \tag{1}$$

The common value is normally distributed with mean μ and variance σ_V^2, i.e. $V \sim N(\mu,\sigma_V^2)$. Likewise, the error terms are i.i.d. draws from $N(0,\sigma_\varepsilon^2)$. The procedure to generate common value signals in (1) appears different from the one used in most previous common value auction experiments (e.g. Kagel and Levin, 1986). In these experiments, the common value *V* is drawn from some prior distribution and bidders receive unbiased signals conditional on the particular realization of *V* (Wilson, 1977). Note, however, that independence of the values and errors in (1) implies that $E(S_i|V) = V + E(\varepsilon_i|V) = V$. Hence, the two formulations are equivalent.

The private value treatment is very similar in structure. Bidder *i*'s signal, S_i, is now the sum of the *individual* value, V_i, and an individual error, ε_i:

$$S_i = V_i + \epsilon_i, \qquad i = 1, \ldots, n. \tag{2}$$

The private values V_i are i.i.d. $N(\mu,\sigma_V^2)$ draws, and the error terms are i.i.d. $N(0,\sigma_\varepsilon^2)$ draws as before. In both the private and the common value treatments, the bidder with the highest signal is predicted to win. However, since bidders' values are the same in the common value treatment, the winning bidder has to realize that she has the largest error draw. In contrast, values are independent in the private value treatment, so winning is not informative in that case. First consider private value auctions for which it is a dominant strategy to bid the object's expected value conditional on the signal: $B^{PV}{}_{Nash}(S_i) = E(V_i \mid S_i) = S_i - E(\varepsilon_i|S_i)$ (the intuition is the same as with no value uncertainty). Normality of the values and errors implies that $\varepsilon|S$ is normally distributed with mean $\mu_{\varepsilon|S} = (S_i - \mu)\,\sigma_\varepsilon^2/(\sigma_\varepsilon^2 + \sigma_V^2)$ and variance $\sigma^2_{\varepsilon|S} = \sigma_\varepsilon^2\,\sigma_V^2/(\sigma_\varepsilon^2 + \sigma_V^2)$. Hence, optimal bids for the private value treatment are linear in the bidder's signal:

$$B^{PV}{}_{Nash}(S_i) = \frac{\sigma_V^2 S_i + \sigma_\epsilon^2 \mu}{\sigma_V^2 + \sigma_\epsilon^2}, \tag{3}$$

Naive bidders who ignore the correlation between signals and errors do not condition on their signal and simply bid their signal: $B_{Naive}(S_i) = S_i$.[8]

8 In a theoretical paper, Compte (2001) independently notices the possibility of a news curse (he refers to the news

Optimal bid levels in common value auctions are such that a bidder is indifferent between winning and losing at that level if the highest of the rivals' bids is of the same level (Milgrom and Weber, 1982). Let Y_1^S (Y_1^ε) denote the highest signal (error) of the N - 1 others. The optimal bids in the common value treatment are: $B^{CV}{}_{Nash}(S_i) = E(V|S_i, Y_1^S = S_i)$, or, equivalently, $B^{CV}{}_{Nash}(S_i) = S_i - E(\varepsilon_i|S_i, Y_1^\varepsilon = \varepsilon_i)$. There is no simple expression for common value Nash bids because the random variable $\varepsilon|S, Y_1^\varepsilon = \varepsilon$ is not normally distributed. It is straightforward, however, to express the optimal bids in terms of the underlying value and error distributions. Let ϕ_V denote the density of the values (with mean μ and variance σ_V^2) and let ϕ_ε be the error density (with mean 0 and variance σ_ε^2) with corresponding distribution Φ_ε. The Nash bids can then be expressed as:

$$B^{CV}{}_{Nash}(S_i) \;=\; S_i \;-\; \frac{\int_{-\infty}^{\infty} \epsilon\, \phi_V(S_i - \epsilon)\, \phi_\epsilon^2(\epsilon)\, \Phi_\epsilon^{N-2}(\epsilon)\, d\epsilon}{\int_{-\infty}^{\infty} \phi_V(S_i - \epsilon)\, \phi_\epsilon^2(\epsilon)\, \Phi_\epsilon^{N-2}(\epsilon)\, d\epsilon}. \tag{4}$$

When bidders neglect the information conveyed by winning (i.e. when they do not realize that their error draw is the largest) and condition on their signal only, they bid the same as in the private value treatment: $B^{CV}{}_{Winner's\ curse}(S_i) = B^{PV}{}_{Nash}(S_i) = S_i - E(\varepsilon_i|S_i)$. The effects of the winner's curse depend on a bidder's signal. Consider, for instance, the case of an extremely low signal, which, without further information, is most likely caused by a small value and a large negative error. The error's expected value is higher, however, when it is the largest of all error draws. Hence, if a bidder ignores that winning implies she has the highest error draw, she will underestimate the error for low signals and bid too high. In contrast, for extremely high signals, a bidder *overestimates* the expected error if she does not realize she can bid up to the point where she beats a rival with the same signal, and hence, the same error. The intuition is that a very high signal could be due to a very high error, but knowing that another bidder has the same error makes a high error less likely, which lowers the error's expected value. To summarize, the winner's curse results in an upward bias in bids for low signals and a downward bias for (very)

curse as the winner's curse in private value auctions).

high signals. Finally, naive bidders, who ignore the correlation between signals and errors simply, bid their signal in the common value treatment: $B_{\text{Naive}}(S_i) = S_i$.

3. Experimental design

The experiment was computerized.[9] Subjects earned points, which were exchanged into guilders at the end of the experiment at a rate of 1 point = 0.75 guilders (about 0.31 US dollars). In total we conducted four treatments. The labels PV and PV+ refer to the private value treatments with inexperienced and experienced subjects, respectively. Likewise, CV and CV+ refer to the inexperienced and experienced common value treatment. Table 1 summarizes the main features of the experimental design.

Bidders were given a starting capital of 40 points, which they did not have to pay back after the experiment. The experiment lasted 30 periods (plus one practice period). In each period subjects were assigned to the same group of bidders, although they did not know this to avoid repeated game considerations. We kept group composition constant for statistical reasons.

At the start of each period a subject received a signal which was the sum of her value (a draw from N(50,100)) and an error term (a draw from N(0,144)). The only difference between common and private value treatments was that in the former values were the same for every bidder in the group, while in the latter values varied independently across bidders. Errors were i.i.d. across subjects and periods and values were i.i.d. across periods and groups (subjects) in the common (private) value treatments. Subjects were completely informed about the procedure used to generate the draws. The information about the distributions was communicated with the help of frequency tables (see Appendix B). Subjects had to answer some questions regarding their understanding of these tables.[10]

Our second-price auction format resembles those used by Amazon.com and Ebay, where bidders place "proxy bids" which commission the auctioneer to buy the commodity at the lowest possible price with a maximum equal to the proxy bid. The bidder can watch the gradual

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[9] The experiment was programmed with the help of the *Rat-Image* Toolbox (Abbink and Sadrieh, 1995).

[10] In the few cases that subjects gave a wrong answer, the experimenter explained the right answer to the subject before the start of the experiment.

Table 1. Summary Experimental Design

treatment	number of groups	number of subjects per group	valuations	errors	subjects' experience
PV	9	4	private: N(50,100)	N(0,144)	none
CV	9	4	common: N(50,100)	N(0,144)	none
PV+	5	4	private: N(50,100)	N(0,144)	once
CV+	5	4	common: N(50,100)	N(0,144)	once

increase of the selling price as other bidders enter their bids.[11] After receiving a signal about the commodity's value, each subject entered her proxy bid, which was restricted to lie between 0 and 100 points.[12] When all subjects had entered their bids, a screen popped up where each of the four subjects in a group was represented by a "thermometer." Bidding started at 0 points at which time the computer randomly assigned the commodity to one of the four bidders. Then the computer repeatedly increased the price by 1 point and rotated the object among the remaining bidders until 3 of the 4 bidders had dropped from the auction. As the computer increased the price, bidders' thermometers increased gradually. When a bidder dropped out of the auction, her thermometer stopped. The winner paid a price equal to the level where the last rival dropped out. At the end of a period, subjects were told their values and their profits for that period.

Subjects and Bankruptcy

Subjects were recruited at the University of Amsterdam. The experiment was finished within 1.5 hours, and subjects earned 45.90 guilders on average (about $19.10). A subject went bankrupt when her cash balance became negative. Subjects knew in advance that they would

[11] An auction with proxy bids is strategically equivalent to a second-price sealed-bid auction, but may be easier to understand.

[12] Without restrictions on the proxy bids, typos can be extremely costly (for instance, a bid of 500 instead of 50 would cause immediate bankruptcy). Since all signals (and values) drawn were between 0 and 100, this procedure does not seem to have limited bidders' relevant bid space.

have to leave the experiment without receiving any money if they went bankrupt. The other group members were informed about a bankruptcy, and the computer replaced this subject for the remainder of the experiment. (Subjects were not informed about how the computer would bid in such a case.) The bankruptcy procedure was common knowledge among the subjects. We do not use the data of a group after a bankruptcy occurred. Only subjects who did not go bankrupt could (voluntarily) subscribe for the experienced treatment. All experienced common (private) value subjects had participated in an earlier common (private) value session.

4. Results

Below we determine the occurrence of the winner's curse (section 4.1) and the news curse (section 4.2) in the different treatments. We also investigate whether the data are consistent with loss/risk aversion or a joy of winning (section 4.3). An explanation of the combined private and common value data is given in section 4.4. First, we discuss general features of the data.

Table 2 presents summary statistics on bids and profits. The data are divided into signals below and above the mean of 50. In the common value treatments there is little evidence for overbidding compared to the risk-neutral Nash prediction, both for low and high signals. Unlike the evidence reported in previous common value experiments, the amount of overbidding is statistically insignificant in the inexperienced treatment, while observed bids are virtually identical to predicted bids in the experienced treatment.[13] Even though the information structure of our common value auctions is no simpler than in previous experiments (i.e. normal versus uniform values and signals), it appears as if bidders suffer from a winner's curse only to a small extent.

The private value data are also surprising. Bids for signals below 50 are substantially below Nash, as would be expected when bidders ignore the correlation between low signals and negative errors. However, bids for signals greater than 50 are remarkably close to Nash, see also

[13] Note, however, that in the inexperienced common value treatment, winners lose some money on average. They earn a positive amount in the experienced common value treatment, although smaller than predicted by Nash. The increase in earnings seems mostly due to more favorable combinations of values and signals as reflected by the higher Nash profits.

Table 2. Some Statistics on Bids and Profits

		CV	CV+	PV	PV+
Bids for signals $\leq$ 50	Actual	38.9	38.6	37.5	38.5
	Nash	37.4 *0.07*	38.2 *0.35*	45.0 *0.01*	44.9 *0.04*
	Naive	37.9 *0.11*	39.1 *0.08*	37.7 *0.51*	37.6 *0.35*
Bids for signals > 50	Actual	55.7	53.9	53.9	55.6
	Nash	54.3 *0.21*	53.8 *0.69*	54.8 *0.68*	55.6 *0.89*
	Naive	62.9 *0.01*	62.2 *0.04*	61.7 *0.01*	63.6 *0.04*
Profits	Actual	-0.38	2.17	4.41	6.49
	Nash	1.84 *0.03*	3.85 *0.04*	3.74 *0.77*	5.80 *0.35*
	Naive	-3.55 *0.01*	-1.53 *0.04*	1.32 *0.09*	2.97 *0.04*

Notes: Each cell displays the average statistic of the particular row-variable and column-treatment. The *p*-value of a Wilcoxon rank test comparing predictions of a particular benchmark model with actual data is displayed in Italics. The average statistic per group is the unit of observation for the test results ($n_{CV}=n_{PV}=9$; $n_{CV+}=n_{PV+}=5$).

Figure 1.[14] At first sight there is a "bad news" curse but no "good news" curse. In section 4.4 we provide an explanation for these surprising results.

We next address the question whether experience matters, and, in particular, how selection and learning affect bidding behavior. The few bankruptcies all occurred in the inexperienced treatments (two in the common value treatment and one in the private value treatment).[15] In the inexperienced common value treatment subjects that participate only once earn on average less profit (-0.56) than subjects that participate twice (0.28). This difference in earnings is

[14] In all the figures, *moving* averages of actual data are displayed: for each signal *j* between 15 and 85 the average bid is based on all the bids that correspond to signals between *j*-2 and *j*+2.

[15] The subject that went bankrupt in PV was the only subject who lacked comprehension of the distributions of values and errors, even after an oral explanation by the experimenter.

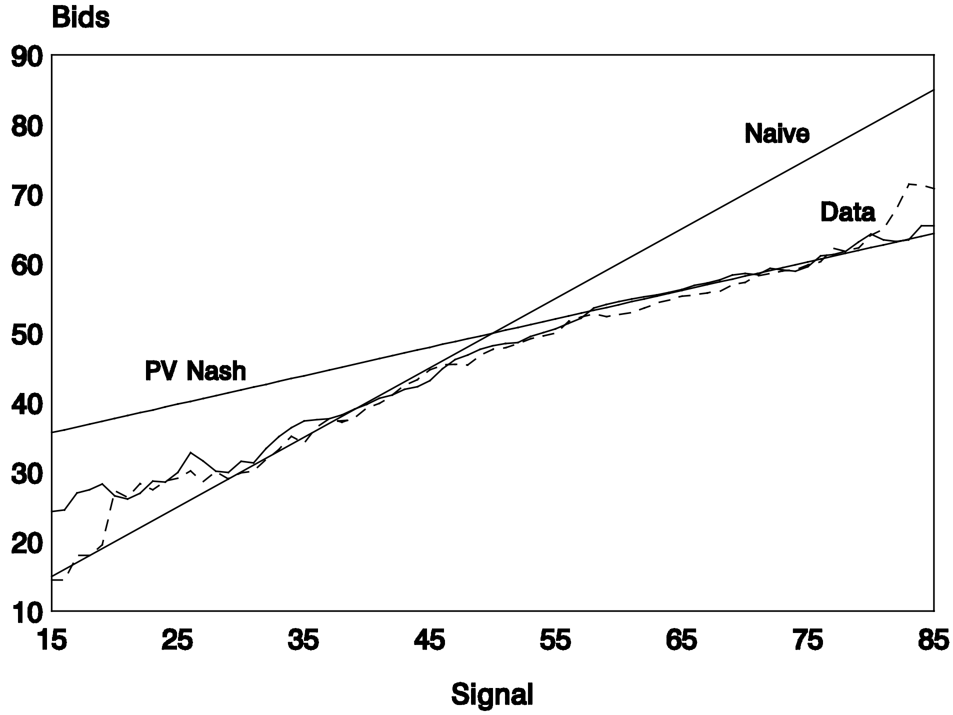

Figure 1. Bids in the Private Value Treatments
Both for Inexperienced (dashed line) and Experienced Subjects (solid line)
Together with Predictions of the Nash and Naive Model

significant (Mann-Whitney p=0.00; n_{once}=16; n_{twice}=20; subjects as unit of observation). A similar selection effect is not observed in the private value treatment. Both in the common and private value treatment, subjects that participated twice earn somewhat higher profits in the experienced treatment than in the inexperienced treatment. However, the differences in actual profits are of the same order as the differences in Nash profits: subjects received more favorable draws in both experienced treatments by chance. Hence there are no clear signs of learning.[16]

There is remarkably little difference between inexperienced and experienced bids, both in the private and the common value auctions. The small difference in private value inexperienced and experienced bids is insignificant at conventional levels (Mann-Whitney p=0.15;

16 We do not want to emphasize these results too much, as it is not yet clear how they generalize across experiments. For example, Goeree and Offerman (2002) report weak signs of both selection and learning. In Cox, Dinkin, Smith and Swarthout (2000) experience makes a difference in the occurrence of the winner's curse in an endogenous entry common value auction.

n_{PV}=1012; n_{PV+}=600), and so is the small difference in common value inexperienced and experienced bids (Mann-Whitney p=0.69; n_{CV}=1076; n_{CV+}=600). The absence of an experience effect is also clear from Figures 1 and 3 and the data table in Appendix A.[17]

4.1. Winner's Curse

Our private value treatment is an ideal control treatment to evaluate a winner's curse in common value auctions. Recall that the only difference between the private and common value treatments is that values are independent in the former while they are the same in the latter. Hence, a comparison between bids across treatments isolates the extent to which bidders fall prey to the winner's curse. Figure 2 displays both the observed and predicted difference between private and common value bids. Since bids in the inexperienced and experienced treatments were the same, we pooled the data of these treatments. As explained in section 2, private value Nash predictions exceed those of the common value treatment for low signals, and this difference is greater for lower signals (since winning is more informative). In contrast, for very high signals the common value Nash predictions are higher. The predicted difference in bids contrasts sharply with the observed difference, which is negligible even for low signals. Moreover, the strong negative trend predicted by Nash is missing in the data.[18] Hence, subjects neglect the fact that winning is informative in the common value treatment.

Appendix A provides a more detailed comparison of private and common value bids, by inexperienced and experienced data and across 20 distinct signal categories. The (economically negligible) differences between actual private and common value bids are also statistically insignificant. Thus our treatments provide clear support for a winner's curse irrespective of confounding factors.

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[17] Our private value treatment with value uncertainty is probably the simplest auction format where inefficiencies should be expected. In equilibrium, the bidder with the highest signal will win even though this bidder need not be the one with the highest value. Realized efficiencies in the experiment, defined as $(PV_{actual}-PV_{min})/(PV_{max}-PV_{min})$, are close to the theoretically expected levels: realized efficiency is 73.5% and 81.6% in PV and PV+, respectively, while theoretical efficiency is 74.7% and 83.6% in PV and PV+, respectively.

[18] The plot of the difference between actual private and common value bids is more volatile for extreme signals, since there are fewer observations at the boundaries. Figure 2 displays moving averages of signals j with at least 20 observations in the interval $[j-2,j+2]$.

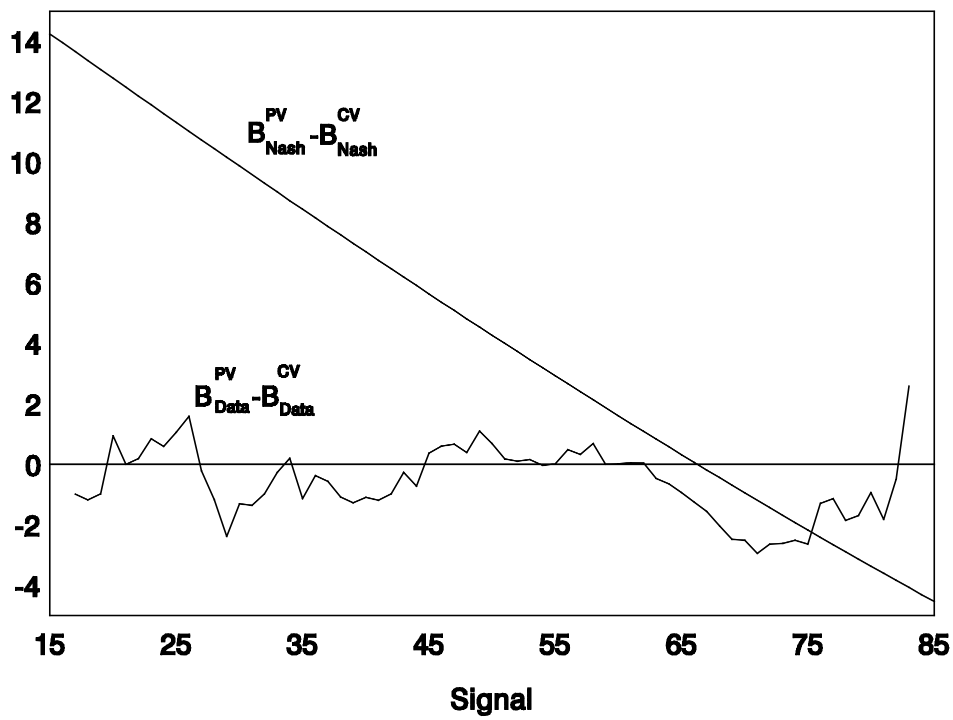

Figure 2. Predicted and Actual Differences in Private and Common Value Bids

4.2. News Curse

When bidders fall prey to the winner's curse as evidenced by the results of the previous section, the private and common value treatments become indistinguishable. In other words, in both treatments, subjects perceive the auctions in which they participate as second-price private value auctions. In this section we use the individual bids to determine to what extent bidders fall prey to the news curse in the different treatments. We analyze the data using two benchmarks: the private value Nash model, based on the assumption that bidders correctly avoid the news curse, and the Naive model, based on the assumption that bidders fall prey to the news curse. Since the data of some of the treatments appear to be "sandwiched" between the Nash and Naive predictions we also test a combined model that allows a fraction of the subjects to fall prey to the news curse.

The Nash and Naive benchmarks make point predictions so an assumption has to be made about how players err in order to evaluate these models. We invoke the common practice of

Table 3. Maximum Likelihood Estimates

		PV n=1012	PV+ n=600	CV n=1076	CV+ n=600	All Data n=3288
PV Nash	σ_{Nash}	10.1	8.4	8.4	7.0	8.8
	-logL	3.74	3.55	3.55	3.36	3.59
Naive	σ_{Naive}	10.5	9.6	9.0	8.2	9.5
	-logL	3.75	3.66	3.61	3.52	3.65
Combined	σ_{Nash}	6.4	4.5	6.6	6.1	6.1
	σ_{Naive}	11.6	9.3	8.9	6.8	9.9
	p	.53	.46	.56	.66	.57
	-logL	3.55	3.33	3.46	3.28	3.45

Notes: The private value Nash model is used to estimate both the private and common value data; *p* represents the probability that a subjects plays according to the Nash model. Mean log likelihood per choice is displayed.

adding a random noise term to the predicted bid. The noise terms are drawn from a truncated Normal distribution with mean 0 and variance σ^2, and are identically and independently distributed across subjects and periods.[19] This method of transforming deterministic models into stochastic models can easily be criticized on theoretical grounds but there is no *a priori* reason why one model is favored over another. So this procedure seems adequate to compare the "goodness-of-fit" of the benchmark models.

Table 3 reports the maximum likelihood estimation results for the different treatments using data from all periods. The final column pertains to the pooled data from the experienced and inexperienced, private and common value treatments. The top panel gives the results for the Nash and Naive benchmarks. Note that Nash provides a better description of the data in all treatments. It seems plausible, however, that there is some heterogeneity among subjects, with some bidders suffering from a news curse while others don’t. This is tested in the combined

[19] The distribution is truncated to ensure that bids stay between zero and one hundred.

model, which allows subjects to bid according to either the Nash or Naive benchmark.[20] This combined model yields a significantly better fit than the Nash model (Likelihood-ratio test: p=0.001) and the Naive model (Likelihood-ratio test: p = 0.001). Assuming the model provides an adequate description of bidding behavior, we can conclude that roughly half of the subjects fall prey to the news curse. In the next section, we allow for loss or risk aversion and show that the resulting model yields similar conclusions with respect to the occurrence of the news curse.

4.3. Non-Linear Utility

In all treatments, subjects bid for an object with an uncertain value. In contrast with standard second-price private value auctions, behavior may therefore be affected by bidders' loss/risk attitudes. In this section we relax the assumption that bidders' utilities are linear and determine optimal bids for arbitrary (increasing) utility functions.

Proposition 1. *Suppose bidders' utilities are given by some increasing utility function, $u(\cdot)$, with $u(0) = 0$. The optimal bids in the private value treatment are then given by*

$$B^{PV}{}_{Nash}(S_i) = \frac{\sigma_V^2 S_i + \sigma_\epsilon^2 \mu}{\sigma_V^2 + \sigma_\epsilon^2} - \Delta_{Nash}. \tag{5}$$

The shift parameter Δ_{Nash} satisfies

$$\int_{-\infty}^{\infty} u(x\,\sigma_{\epsilon|S} + \Delta_{Nash})\,\phi(x)\,dx = 0, \tag{6}$$

where $\sigma^2_{\varepsilon/S} = \sigma_\varepsilon^2\,\sigma_V^2/(\sigma_\varepsilon^2 + \sigma_V^2)$ and $\phi(\cdot)$ is the density for a standard normal variable.

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[20] To be precise, the unconditional likelihood $L(x_{i,1},\ldots,x_{i,30})$ of player i's choices $x_{i,t}$ of the combined model in periods 1-30 is:

$$L(x_{i,1},\ldots,x_{i,30}) = p \prod_{t=1}^{30} L(x_{i,t}|Nash) + (1-p) \prod_{t=1}^{30} L(x_{i,t}|Naive),$$

where $L(x_{i,t}|Nash)$ represents the conditional probability of $x_{i,t}$ predicted by the Nash model, $L(x_{i,t}|Naive)$ represents the conditional probability of $x_{i,t}$ given the Naive model, and p is the probability that a subject plays according to the Nash benchmark. The Nash and Naive benchmarks are nested as special cases (i.e. $p = 1$ or $p = 0$).

In other words, non-linearities of the utility function merely result in a parallel shift of the optimal bidding function.[21] The shift parameter, Δ_{Nash}, may be interpreted as a "prize premium." Indeed, (6) implies that an individual is indifferent between accepting or rejecting a bet that involves normally distributed prizes (with variance $\sigma^2_{\varepsilon|S}$) only when all prizes are uniformly increased by Δ_{Nash}. It is readily verified that Jensen's inequality implies that prize premiums are positive (negative) for concave (convex) utility functions. Note, however, that different utility functions may result in the same prize premium and hence in the same optimal bids.[22] For instance, any anti-symmetric utility function that satisfies $u(-x) = -u(x)$ yields the risk-neutral bidding function given by (3).

For a naive bidder, non-linearities of the utility function also result in a parallel shift of the optimal bidding function: $B_{Naive}(S_i) = S_i - \Delta_{Naive}$, where Δ_{Naive} satisfies

$$\int_{-\infty}^{\infty} u(x\,\sigma_\varepsilon + \Delta_{Naive})\,\phi(x)\,dx = 0. \tag{7}$$

Since $\sigma_\varepsilon > \sigma_{\varepsilon|S}$, the prize premium will be higher for a naive bidder than for a rational bidder with the same concave utility function. Moreover, different utility functions will in general result in different predictions for the ratio, $\Delta_{Nash}/\Delta_{Naive}$. To illustrate this point, we will consider three alternative specifications for bidders' risk preferences: constant absolute risk aversion, loss aversion, and a joy of winning. These models are commonly employed to explain deviations from risk-neutral Nash bids.

First, consider the case of constant absolute risk aversion (CARA): $u(x) = (1\text{-}\exp(-r\,x))/r$, where r is a risk parameter. The prize premiums are then: $\Delta_{Nash} = ½\, r\, \sigma^2_{\varepsilon|S}$ and $\Delta_{Naive} = ½\, r\, \sigma^2_\varepsilon$ so that $\Delta_{Nash}/\Delta_{Naive} = (\sigma_{\varepsilon|S}/\sigma_\varepsilon)^2$. A model of "loss aversion" (Tversky and Kahneman, 1991) is based on the idea that people weigh losses more heavily than gains. A utility function that captures such preferences is given by $u(x) = x$ for $x \geq 0$ and $u(x) = (1 + \alpha)\, x$ for $x < 0$, where α is the coefficient of constant loss aversion. There are no simple expressions for Δ_{Nash} and Δ_{Naive} for

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[21] See Appendix B for a proof of Proposition 1.

[22] This is similar to the result that in standard second-price auctions without value uncertainty, bidding one's value is a weakly dominant strategy irrespective of risk attitudes.

Table 4. Maximum Likelihood Estimates

		PV n=1012	PV+ n=600	CV n=1076	CV+ n=600	All Data n=3288
Joy-of-Winning Model	$\sigma_{\text{PV Nash}}$	5.1	4.6	6.7	4.8	5.3
	σ_{Naive}	10.0	8.5	7.4	4.9	8.9
	δ	-3.6	-2.7	-3.1	-4.2	-3.7
	p	.39	.55	.58	.61	.52
	-logL	3.45	3.24	3.38	3.02	3.34
Loss Aversion Model	$\sigma_{\text{PV Nash}}$	5.1	4.1	6.3	4.8	5.1
	σ_{Naive}	9.9	8.2	8.0	4.9	8.9
	α	1.71	1.06	1.22	1.98	1.57
	p	.39	.45	.56	.57	.52
	-logL	3.45	3.23	3.38	3.02	3.33
Risk Aversion Model	$\sigma_{\text{PV Nash}}$	5.9	4.1	6.3	4.9	5.8
	σ_{Naive}	9.4	8.1	8.1	4.9	8.1
	r	.08	.06	.06	.08	.08
	p	.47	.45	.57	.56	.58
	-logL	3.45	3.22	3.38	3.03	3.34

Notes: The private value Nash model is used to estimate both the private value and the common value data; *p* represents the probability that a subjects plays according to the Nash model. Mean log likelihood per choice is displayed.

this utility function but it is straightforward to show that $\Delta_{\text{Nash}}/\Delta_{\text{Naive}} = \sigma_{\varepsilon|S}/\sigma_{\varepsilon}$.[23] Finally, it is easy to see how bids change when bidders experience a joy of winning, which simply raises the object's value by an amount $\delta \geq 0$. Since it is an optimal strategy for risk neutral bidders to bid the object's expected value, the shifts are now: $\Delta_{\text{Nash}} = \Delta_{\text{Naive}} = -\delta$, so that $\Delta_{\text{Nash}}/\Delta_{\text{Naive}} = 1$. Note that a joy of winning raises the optimal bids.

[23] The shift for the Nash benchmark is the unique fixed point of

$$\Delta_{Nash} = \alpha\, \sigma_{\varepsilon|S} \int_{\Delta_{Nash}}^{\infty} (1 - \Phi(x))\, dx,$$

where $\Phi(\cdot)$ is the cumulative of a standard normal variable. The shift for the Naive benchmark satisfies a similar fixed point equation with $\sigma_{\varepsilon|S}$ replaced by σ_{ε}.

Table 4 reports how well each model explains the data. In each case we allow a fraction of the bidders to fall prey to the news curse. The inclusion of the CARA parameter significantly improves the fit in all cases (cf. Table 3: Likelihood-ratio test, $p < 0.01$ for each case) and the estimated CARA parameter is stable across the different treatments, with a pooled estimate of $r = .08$. Similar results are obtained for the loss aversion model, with a pooled estimate of $\alpha = 1.57$. The fit of the joy-of-winning model is almost as good, but the model predicts a *negative* joy of winning and is therefore rejected. The estimates for the proportion of naive players, $1 - p$, hardly differ for inexperienced and experienced data, which suggests that the news curse does not disappear with experience. Finally, roughly one-half of the subjects fall prey to this curse.[24]

4.4. Explaining the Combined Private and Common Value Data

If we had only conducted common value auctions without the private value benchmark, we might very well have drawn erroneous conclusions from the data. Figure 3 displays average bids in the inexperienced and experienced common value treatments together with the common value Nash predictions. For those familiar with the results of previous common value auction experiments, these results must seem striking. There is only slight overbidding relative to Nash in the inexperienced treatment, while observed bids are virtually equal to predicted bids in the experienced treatments. In other words, there appears to be hardly a winner's curse! This finding contrasts sharply with Figure 2, which provides strong proof for a winner's curse.

Figure 4 presents the correct explanation for the combined private and common value data. In this figure, the data of the inexperienced and experienced treatments are pooled. In addition, the (private value) Nash and Naive benchmarks are corrected using the loss aversion parameter estimated from the pooled data ($\alpha = 1.57$). Loss aversion pushes the benchmarks down, which resolves the apparent asymmetry between low and high signals noted for the private

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[24] Table 4 shows that constant absolute loss aversion and constant absolute risk aversion explain our data equally well. Nevertheless, the implications of loss aversion and CARA for larger gambles are quite different. For instance, a loss averse person who is indifferent between accepting or rejecting a 50-50 bet of \$2 and -\$1 is also indifferent over a 50-50 bet of \$200 and -\$100. This scale invariance certainly does not hold under the CARA assumption, which predicts that a person indifferent between accepting or rejecting a 50-50 bet of \$2 and -\$1 strongly rejects a 50-50 bet of \$200 and -\$100. Indeed, as Rabin (2000) points out, constant absolute risk aversion may yield implausible predictions when extrapolated from small to large stakes. For this reason, one may prefer the loss aversion model even though the CARA model provides an equally good fit of the data.

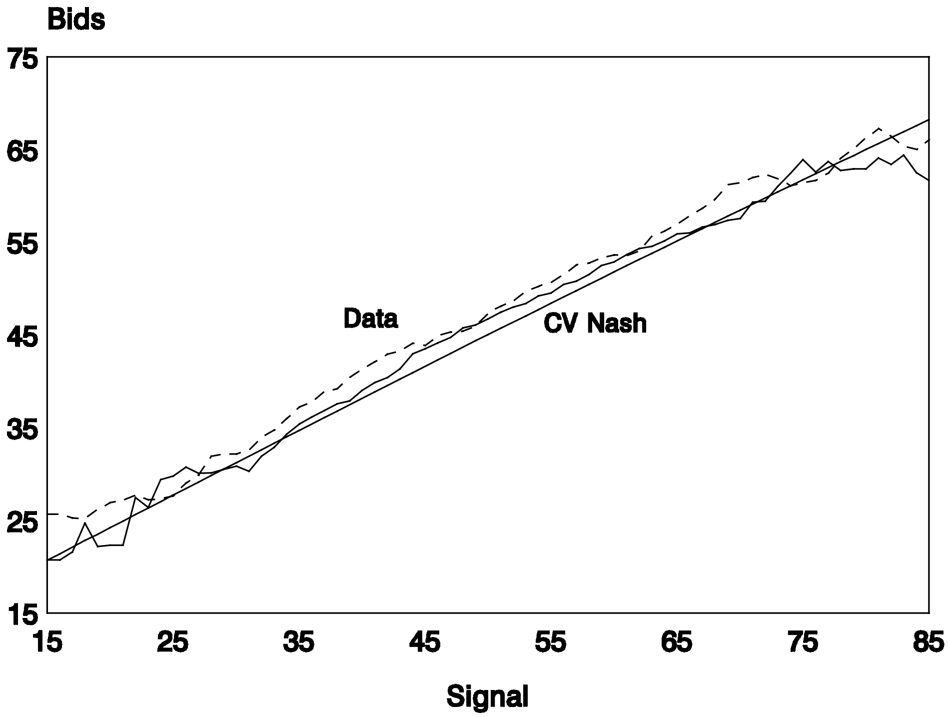

Figure 3. Bids for Inexperienced (dashed) and Experienced (solid) Common Value Treatments Together with Common Value Nash Bids

value treatment: loss-averse bidders fall prey to both a "good news" curse and a "bad news" curse. Indeed, the corrected benchmarks sandwich the actual data.[25] Next, we allow for a partial news curse by taking the weighted average of the Nash and Naive predictions, where the weight on the rational bids is given by the pooled estimate $p = .52$ (see Table 4). This results in the thick solid line of Figure 4, which is almost indistinguishable from the actual data. Interestingly, the thick solid line is also close to the common value Nash predictions, which creates the illusion that subjects do not fall prey to a winner's curse. In fact they do: in the common value auction subjects bid as if it were a private value auction (Figure 2), their bids reflect aversion to losses or risk, and they fall prey to a (partial) news curse.

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[25] Correcting the benchmarks for risk aversion results in a very similar figure.

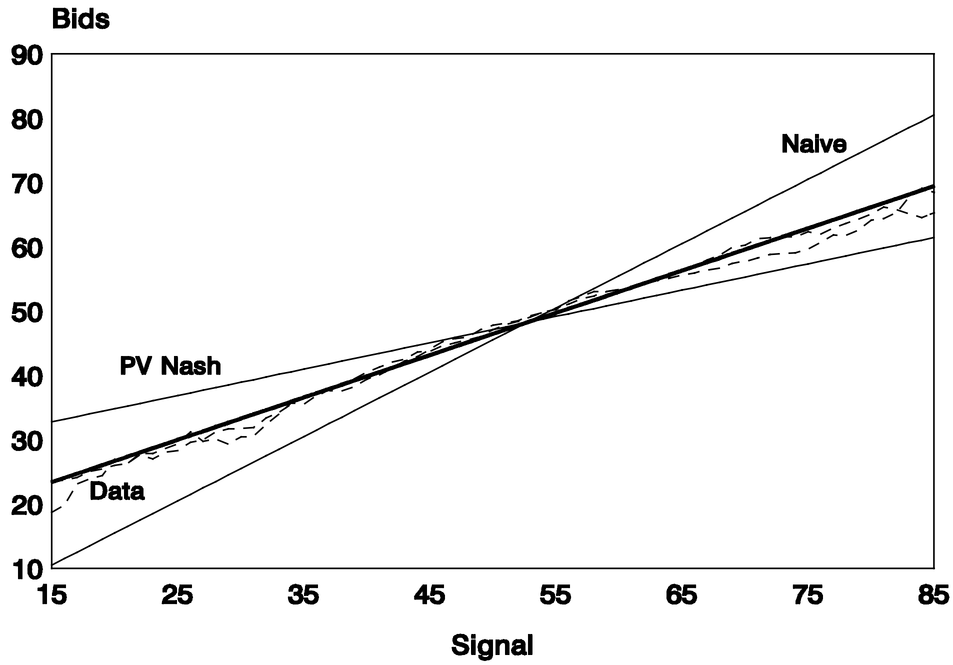

Figure 4. Bids in Private/Common Value Treatments (dashed)
Nash/Naive Predictions Corrected for Loss Aversion (solid) and News Curse (thick)

5. Conclusion

This paper considers auctions where bidders are not completely certain about their values for the commodity for sale. Our experiment employs two parallel treatments, one in which values are independent across bidders (the private value treatment) and one in which all values are the same (the common value treatment). Three primary conclusions arise from comparing bidding behavior in the private and common value treatments.

First, our private value treatment provides an ideal control for common value auctions in that it yields a direct evaluation of the winner's curse. The evidence presented in this paper is very clear: in the common value treatments, subjects bid the same as in the private value treatments.

Second, our design allows one to investigate the possibility of a news curse, which occurs when bidders neglect the fact that a high (low) signal makes a positive (negative) error more likely. Roughly half the subjects are estimated to fall prey to the news curse, which correctly predicts the direction of deviations in bids.

Third, the value uncertainty present in our second-price private value treatment makes it possible to discriminate between loss/risk aversion and a joy of winning. While loss/risk aversion results in a downward parallel shift of the bidding function, a joy of winning shifts the bidding function upward. The data clearly favor the loss/risk aversion explanation.

Previous common value auction experiments employed uniformly distributed values and signals, which precludes the possibility of a news curse. These studies typically find a dramatic effect of the winner's curse on bidders' performance. In contrast, when common value values and signals are normally distributed, the news curse may alleviate the effects of a winner's curse in second-price (English) auctions. The intuition is that for low signals, a winner's curse raises bids while a news curse lowers bids (since "bad news" is taken at face value without realizing it is partly caused by a negative error). For (very) high signals, a winner's curse *lowers* bids (see section 2), and again its effects are mitigated by a news curse that yields an upward bias for high signals. Due to these counter prevailing effects, there is almost no overbidding in our common value treatments *even though bidding behavior in the common value treatments is identical to that in the private value treatments* (see Figures 2 and 4). In other words, with normally distributed values and signals, observed bids may be winner's cursed even when they are close to Nash predictions.

This insight may explain the discrepancy between the mixed findings of empirical studies and the unambiguous results obtained in previous experiments. In real-world settings, the distribution of common values and signals is unlikely to be uniform and a news curse may counteract the effects of a winner's curse. Indeed, it may be impossible to rule out winner's curse behavior in field data: even when there is no apparent overbidding, the winner's curse may be alive and well.

References

Abbink, Klaus and Abdolkarim Sadrieh (1995) "Ratimage, Research Assistance Toolbox for Computer-Aided Human Behavior Experiments," *Discussion paper B-325*, University of Bonn.

Ashenfelter, Orley and David Genesove (1992), "Testing for Price Anomalies in Real-Estate Auctions," *American Economic Review: Papers and Proceedings*, *82*, 501-5.

Avery, Christopher and John H. Kagel (1997), "Second-Price Auctions with Asymmetric Payoffs: An Experimental Investigation," *Journal of Economics and Management Strategy*, *6*(3), 573-603.

Barut, Yasar, Dan Kovenock, and Charles Noussair (1999), "A Comparison of Multiple-Unit All-Pay and Winner-Pay Auctions Under Incomplete Information," *International Economic Review, forthcoming*.

Bazerman, Max H. and William F. Samuelson (1983), "I Won the Auction But Don't Want the Prize," *Journal of Conflict Resolution*, *27*(4), 618-34.

Camerer, Colin F. (1987) "Do Biases in Probability Judgments Matter in Markets? Experimental Evidence," *American Economic Review*, *77*, 981-997.

Camerer, Colin F. (1995), "Individual Decision Making," in J.H. Kagel and A.E. Roth, eds., *The Handbook of Experimental Economics*, Princeton: Princeton University Press, 587-616.

Capen E.C., R.V. Clapp and W.M. Campbell (1971), "Competitive Bidding in High-Risk Situations," *Journal of Petroleum Technology*, *23*, 641-53.

Cason, Timothy N. (1995), "An Experimental Investigation of the Seller Incentives in EPA's Emission Trading Auction," *American Economic Review*, *85*, 905-922.

Chen, Kay-Yut, and Charles R. Plott, (1998), "Nonlinear Behavior in Sealed Bid First Price Auctions," *Games and Economic Behavior*, *25*(1), 34-78.

Cox, James C., Vernon L. Smith, Samuel H. Dinkin and James T. Swarthout (2000), "Endogenous Entry and Exit in Common Value Auctions," working paper, University of Arizona.

Compte, Olivier (2001), "The Winner's Curse with Private Values," working paper, CERAS, Ecole Nationale des Ponts et Chausées.

Dyer, Douglas, John H. Kagel and Dan Levin (1989), "A Comparison of Naive and Experienced Bidders in Common Value Offer Auctions," *Economic Journal*, *99*, 108-15.

El-Gamal, Mahmoud A. and David M. Grether (1995), "Are People Bayesian? Uncovering Behavioral Strategies," *Journal of the American Statistical Association*, *90*, 1137-45.

Garvin, Susan and John H. Kagel (1994), "Learning in Common Value Auctions: Some Initial Observations," *Journal of Economic Behavior and Organization*, *25*, 351-72.

Goeree, Jacob K. and Theo Offerman (2002), "Efficiency in Auctions with Private and Common Values: An Experimental Study," *American Economic Review*, forthcoming.

Grether, David M. (1980), "Bayes Rule as a Descriptive Model: The Representativeness Heuristic," *Quarterly Journal of Economics*, *95*, 537-57.

Holt, Charles A. and Roger Sherman (2000), "Risk Aversion and the Winner's Curse," working paper, University of Virginia.

Kagel, John H. (1995), "Auctions: A Survey of Experimental Research," in J.H. Kagel and A.E. Roth, eds., *The Handbook of Experimental Economics*, Princeton: Princeton University Press, 501-85.

Kagel, John H. and Dan Levin (1986), "The Winner's Curse and Public Information in Common Value Auctions," *American Economic Review*, *76*, 894-920.

Kagel, John H. and Dan Levin (1993), "Independent Private Value Auctions: Bidder Behaviour in First-, Second- and Third-Price Auctions With Varying Numbers of Bidders," *Economic Journal*, *103*, 868-879.

Kagel, John H. and Dan Levin (1999), "Common Value Auctions with Insider Information," *Econometrica*, *67*(5), 1219-38.

Kagel, John H., Dan Levin, and Ronald M. Harstad (1995), "Comparative Static Effects of Number of Bidders and Public Information on Behavior in Second-Price Common Value Auctions," *International Journal of Game Theory*, *24*, 293-319.

Kagel, John H., Dan Levin, Raymond C. Battalio and Donald J. Meyer (1989), "First-Price Common Value Auctions: Bidder Behavior and the Winner's Curse," *Economic Inquiry*, *27*, 241-58.

Kwasnica, Anthony M. (2000), "The Choice of Cooperative Strategies in Sealed Bid Auctions," *Journal of Economic Behavior and Organization*, *42*, 323-346.

Levin, Dan, John H. Kagel and Jean-Francois Richard (1996), "Revenue Effects and Information Processing in English Common Value Auctions," *American Economic Review*, *86*, 442-60.

Lind, Barry and Charles R. Plott (1991), "The Winner's Curse: Experiments with Buyers and with Sellers," *American Economic Review*, *81*(1), 335-46.

McAfee, R. Preston and John McMillan (1987), "Auctions and Bidding," *Journal of Economic Literature*, *25*, 699-738.

Milgrom, Paul R. and Robert J. Weber (1982), "A Theory of Auctions and Competitive Bidding," *Econometrica*, *50*(5), 1089-1121.

Palfrey, Thomas R. (1985), "Buyer Behavior and the Welfare Effects of Bundling by a Multiproduct Monopolist: A Laboratory Investigation," in V.L. Smith, ed., *Research in Experimental Economics*, *3*, Greenwich, CT: JAI Press, 73-104.

Rabin, Matthew (2000) "Risk Aversion and Expected-Utility Theory: A Calibration Result," *Econometrica*, *68*(5), 1281-92.

Roll, Richard (1986) "The Hubris Hypothesis of Corporate Takeovers," *Journal of Business*, *59*(2), 197-216.

Thaler, Richard H. (1988) "Anomalies: The Winner's Curse," *Journal of Economic Perspectives*, *2*(1), 191-202.

Tversky, Amos and Daniel Kahneman (1982) "Evidential Impact of Base Rates," in D. Kahneman, P. Slovic and A. Tversky, eds., *Judgment under Uncertainty: Heuristics and Biases*, Cambridge: Cambridge University Press, 153-160.

Tversky, Amos and Daniel Kahneman (1991) "Loss Aversion in Riskless Choice: A Reference-Dependent Model," *Quarterly Journal of Economics*, *106*(4), 1039-61.

Wilson, Robert (1977) "A Bidding Model of Perfect Competition," *Review of Economic Studies*, *44*, 551-518.

Appendix A. Private Value Bids versus Common Value Bids

signals	CV bids	PV bids	p	CV+ bids	PV+ bids	p	Δ_{Nash}
0-5	19.6 *(5)*	9.2 *(5)*	0.21	17.5 *(2)*	18.5*(2)*	1.00	18.4
6-10	19.5 *(6)*	22.3 *(6)*	0.47	25.0 *(1)*	30.0 *(1)*	0.32	16.3
11-15	21.0 *(4)*	8.8 *(4)*	0.11	--	21.6 *(5)*	--	15.0
16-20	25.3*(16)*	18.0 *(9)*	0.10	24.7 *(7)*	27.5*(15)*	0.45	13.3
21-25	27.2 *(34)*	27.5 *(31)*	0.93	26.4 *(12)*	28.7 *(16)*	0.40	11.7
26-30	31.9 *(41)*	30.1 *(53)*	0.25	30.1 *(24)*	30.1 *(27)*	0.36	10.5
31-35	34.8 *(93)*	33.2 *(73)*	0.33	32.9 *(36)*	35.1 *(47)*	0.01	8.9
36-40	39.2 *(103)*	37.2 *(94)*	0.27	37.6 *(53)*	38.2 *(60)*	0.08	7.9
41-45	43.3 *(128)*	42.5 *(112)*	0.31	41.3 *(82)*	41.9 *(62)*	0.06	6.3
46-50	45.4 *(152)*	45.4 *(126)*	0.62	45.8 *(74)*	46.8 *(77)*	0.27	4.9
51-55	49.7 *(109)*	49.2 *(143)*	0.51	48.4 *(82)*	49.5 *(70)*	0.07	3.6
56-60	52.8 *(131)*	52.7 *(117)*	0.43	51.5 *(66)*	53.6 *(66)*	0.01	2.3
61-65	55.7 *(89)*	54.3 *(95)*	0.02	54.6 *(75)*	55.5 *(51)*	0.26	1.1
66-70	59.6 *(64)*	56.0 *(60)*	0.00	56.9 *(32)*	57.7 *(42)*	0.52	-0.3
71-75	61.9 *(47)*	58.9 *(50)*	0.04	61.0 *(23)*	59.1 *(20)*	0.29	-1.5
76-80	64.1 *(31)*	61.7 *(19)*	0.26	62.8 *(18)*	61.8 *(14)*	0.41	-3.0
81-85	65.3 *(21)*	71.4 *(13)*	0.06	64.4 *(5)*	63.5 *(11)*	0.82	-4.0
86-90	--	52 *(1)*	--	66.0 *(4)*	69.7 *(9)*	0.28	-5.7
91-95	--	--	--	66.3 *(3)*	63.5 *(2)*	0.76	-5.5
96-100	68.5 *(2)*	54 *(1)*	0.22	70 *(1)*	89.7 *(3)*	0.18	-6.8
0-100	46.6 *(1076)*	45.6 *(1012)*	0.27	46.5 *(600)*	46.7 *(600)*	0.37	4.7

Notes: The number of observations in each signal category is displayed in italics in parentheses. The *p*-value of a Mann-Whitney test comparing the bids in the private and common value treatments are displayed. The final column gives the difference in Nash bids for the two treatments: $\Delta_{Nash} = B^{PV}_{Nash} - B^{CV}_{Nash}$.

Appendix B. Proof of Proposition 1.

Suppose players $i = 2,...,N$ use the proposed bidding function $B(\cdot)$ given by equation (5). When player 1's signal is s and she bids as if her signal is t, her expected payoffs are

$$\pi^e{}_1(\boldsymbol{B}(t),s) \;=\; \int_{-\infty}^{t}\int_{-\infty}^{\infty} u(s - \epsilon - \boldsymbol{B}(y))\, f(\epsilon\,|\,s)\, d\epsilon\, f(y)\, dy. \tag{A1}$$

Differentiating this expression with respect to t and evaluating the result at $t = s$ yields the first-order condition

$$\int_{-\infty}^{\infty} u(E(\epsilon\,|\,s) - \epsilon + \Delta_{Nash})\, f(\epsilon\,|\,s)\, d\epsilon \;=\; 0, \tag{A2}$$

where we used that the bidding function in (5) can be written as $B(s) = s - \mathrm{E}(\varepsilon\,|\,s) - \Delta_{\mathrm{Nash}}$. Recall that $f(\varepsilon\,|\,s)$ is a normal density with mean $\mathrm{E}(\varepsilon\,|\,s)$ and variance $\sigma^2_{\varepsilon|\mathrm{S}}$, so $x = (\mathrm{E}(\varepsilon\,|\,s) - \varepsilon)/\sigma_{\varepsilon|\mathrm{S}}$ is a standard normal variable with density $\phi(x)$ and (A2) can be rewritten as

$$\int_{-\infty}^{\infty} u(x\,\sigma_{\epsilon|S} + \Delta_{Nash})\, \phi(x)\, dx \;=\; 0, \tag{A3}$$

The naive bids in (7) can be derived in a similar way.