The Common-Probability Auction Puzzle*

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Abstract

This paper presents a puzzle in the behavior of experimental subjects in what we call common-probability auctions. In common-value auctions, uncertainty is defined over values while, in common-probability auctions, uncertainty is defined over probabilities. We find that in contrast to the substantial overbidding found in common-value auctions, bidding in strategically equivalent common-probability auctions is consistent with Nash-equilibrium. In our experiments we isolate the different steps of reasoning involved in the bidding process and conclude that in competitive environments the difference in bids across our two auctions stems from differences in the way subjects value the objects they are bidding for rather than the way they bid conditional on these valuations.

JEL-Classification: D44, D81, C70, C90
Keywords: Common-value auction, winner's curse, uncertain values, uncertain probabilities, compound lotteries, bid, strategic uncertainty, motivated reasoning.

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1 Introduction

In the typical common-value auction a good is sold whose unknown value is common to all bidders. Each bidder receives a signal about the value drawn from a commonly known distribution and, based on the signal received, makes a bid. This way of modeling auctions has been motivated, for instance, by the famous example of bidding for oil rights among oil companies. In this paper we continue to call such auctions with common uncertainty about a value "common-value (CV)" auctions.

However, in many settings, common-value auctions also exist in situations where the value of the good is known but the common probability with which such a common value will be realized is uncertain. For example, consider firms bidding for bonds issued by a corporation under financial stress. Here the value of the bond at maturity is known but what is uncertain is the probability of default by the corporation. If investors do their due diligence they will receive a signal about the common default risk drawn from a commonly known distribution and, based on this probability signal, make a bid for the bond. In such situations the uncertainty involved in the auction is reversed – the bidders know the value of the good but are ignorant of the common default risk. What is uncertain is a common probability and not a common value. We call such auctions "common-probability (CP)" auctions.

Many other examples of common-probability auctions exist. For example, in auctions for artwork or antiques with dubious provenance collectors might have a precise assessment of the object's value provided its provenance is good, but the same object is worthless if it is counterfeit or stolen. The main uncertainty comes then from not knowing the odds of an immaculate provenance. Similarly, in many auctions for goods or contracts with contingencies the major uncertainty is about the probability that an event will occur (see Cong, 2020). For instance, consider a real estate developer who is thinking of bidding on a piece of rural land with the hope of building a shopping center. The developer knows the value of the land in that use but a shopping center is only viable if a highway being discussed by the state highway commission is built. If the highway is not built, the land remains farmland. The uncertainty here is over the probability of the highway being built and not its value contingent on that happening. Other contingent entities might be firms who create a new product whose value is contingent on their receipt of a patent. The worth of the firm can be estimated fairly accurately once the patent is granted, but the uncertainty over whether it will be is the vehicle driving the firm's value. To include such ex-post uncertainty into the sale of these contingent products, it is possible to auction off contingency contracts, and a recent and interesting literature on such auctions with contingent bids exists (see, e.g., DeMarzo et al., 2005). Yet, in many cases goods are auctioned with all-cash bids, i.e., without the use of such contracts. Finally, there are many cases where what is being auctioned is a hybrid of our two auction types, with uncertainty over both values and probabilities, but often one object of uncertainty prevails over the over one.

The question we ask in this paper is whether, in auctions, bidders process these two objects of uncertainty in the same way. In other words, do bidders, when facing two strategically equivalent common-value and common-probability auctions, submit identical bids or does the fact that one auction exhibits uncertainty in the value domain while the other exhibits it in the probability domain lead to differences in bidding behavior?

In the different treatments of our experiment subjects face either CV or CP auctions and bid for equivalent items. In CP auctions we present subjects with a random asset whose value is known but where the probability of receiving that value is not, while in CV auctions our subjects face a different asset whose failure risk is known but whose value in the case of success is uncertain. These assets define lotteries for which our subjects bid and are strategically equivalent in that bidders should have identical expectations conditional on equivalent probability and value signals and, hence, bid identically.

What we find is interesting. First, in contrast to the theoretical predictions, our subjects' bids in CV auctions are significantly higher than their bids in equivalent CP auctions. More specifically, while our subjects in CV auctions tend to bid above the naïve bidding function (i.e., bidding the expected value given the signal), subjects in CP auctions tend to bid below the even lower risk-neutral Nash equilibrium bid function. As a result, winning bidders are less vulnerable to the winners' curse in the CP than in the CV auction due to their less aggressive bidding. Why this difference exists is the puzzle we wish to unravel in this paper.

To investigate our puzzle we break down the bidding process into two stages, one dealing with fundamental uncertainty (Stage 1) and the other with strategic uncertainty (Stage 2), and ran treatments attempting to identify which stage is responsible for our puzzle. In Stage 1, bidders have to calculate their subjective valuation for the good given a signal. This task requires them to solve the problem of fundamental uncertainty as they have to estimate how much the good is actually worth. Once they have formed their subjective estimate, in Stage 2, they then have to convert this subjective valuation into a strategic bid, taking into account how others will bid. This second task deals only with strategic uncertainty.

The difference in bidding may emanate from either or both of these two stages. In the first stage, subjects possibly value the lotteries with uncertain values differently than those with uncertain probabilities conditional on identical signals. Alternatively, given identical valuations in Stage 1, in Stage 2 bidders may view the strategic uncertainty across our two settings differently and bid accordingly.

In our experimental design, Experiment I establishes our main result of the asymmetry of bidding behavior across our CV and CP auctions. To sort out whether this difference originates in Stage 1 we ran Experiment II where subjects are asked to simply evaluate (price) the same lotteries underlying our CV and CP auctions but not bid for them in an auction. By stripping the auction game of its strategic elements we can assess to what extent fundamental uncertainty is responsible for the difference in bids observed.

We then ran two more experiments to study the auction context specifically. Experiment III investigates how bidders resolve the Stage-1 problem of fundamental uncertainty in an auction (competitive) as opposed to the (non-competitive) decision problem studied in Experiment II. In this experiment subjects first engage in 40 rounds of auctions, and then estimate, *inter alia*, a lottery's average payoff knowing that their signal was one of four existing signals about the lottery in a market. Since these subjects were experienced in bidding in auctions, their valuations should reflect that experience and, hence, demonstrate how being placed in an auction setting affects valuations. In Experiment IIIb we reverse the order of Experiment III and have the subjects estimate the lottery's worth conditional on signals (again knowing it is one of four generated signals) before bidding for another set of lotteries. In this experiment, when subjects submitted their estimates, they did not know that they would subsequently engage in an auction. The difference in estimates between Experiments III and IIIb should reflect the influence of bidding competition on lottery valuation.

Finally, in Experiment IV, we switch our focus to Stage 2 and study how bidders deal with the strategic uncertainty inherent in the auction game. Here our objective is to assess the importance of strategic uncertainty relative to fundamental uncertainty, thereby gauging the extent to which resolving the problem of fundamental uncertainty is sufficient to eliminate differences in bids across our auctions. We do this by looking at two different objects. One is how bids adjust once we provide subjects with the objectively correct Stage-1 valuations. Another is whether subjects expect competition to differ across auction formats; We therefore elicit what subjects consider to be the highest bid of their competitors.

Our experiments reveal that differences in bids originate by and large in the first stage of the bidding process–but only when facing competition. When placed in an auction context, subjects resolve uncertain values differently from uncertain probabilities. While they form correct estimates with uncertain probabilities, misjudgments arise with uncertain values. More precisely, in CV auctions, our subjects overestimate the lottery's expected payoff but only in a competitive setting of Experiment III as opposed to the non-competitive settings of Experiments II and IIIb.

The fact that in Stage 1 of our CV auctions bidders overvalue lotteries is neither necessary nor sufficient for overbidding in Stage 2. This would only be true if in Stage 2 subjects believed that their opponents also overvalued the good and bid aggressively given these exaggerated valuations. Such beliefs (among other things) were the focus of Experiment IV, where we find that, in our CV auction, our subjects expected their competitors to bid above the lottery's objective value and theses beliefs were confirmed. Such high beliefs and overbidding were not present in our CP auctions. One final observation is that bidding behavior did not differ across our CP and CV auctions in the sense that, given their valuations, the degree to which subjects shaved their bids was similar. This again places overbidding in CV auctions at the feet of overvaluation in Stage 1, with the caveat that this overvaluation only occurs in a competitive (strategic) context.

Our paper is connected to a number of different literatures. First, there is the obvious connection to the literature on common-value auctions and the extensive evidence on the winners' curse (Kagel and Levin 1986; Kagel et al. 1989; Charness and Levin 2009; Charness et al. 2014, i.a.; see also

Kagel and Levin 2002 for an excellent review). This pervasive observation in the laboratory has spiked a wide experimental literature testing its robustness and, so far, the winner's curse effect was found to decline with public information (Kagel and Levin, 1986; Grosskopf et al., 2018), learning in form of sufficient experience (Dyer et al., 1989; Kagel and Richard, 2001; Casari et al., 2007) or familiarity with the task in the field (Harrison and List, 2008).[1] Our contribution here is to investigate the extent to which the winners' curse is robust to having stochastic rather than deterministic objects auctioned off. Having lotteries as auction prizes allows for modeling the common uncertainty in two alternative ways, either as common probabilities or as common values. Our experimental findings are unprecedented because they directly connect the incidence of the winner's curse to the object up for sale. We demonstrate that persistent overbidding is eliminated in an equivalent variant of the same game that requires identical skills of Bayesian updating, contingent reasoning and learning.

The main drivers of the winner's curse phenomenon are still subject to a debate. The experimental literature provides mixed evidence on the importance of emotions like the thrill of winning (Cox et al., 1992; Holt and Sherman, 1994; Bos et al., 2008; Astor et al., 2013) or the fear of losing (Delgado et al., 2008). Other explanations offered relate more directly to strategic uncertainty. For instance, subjects possibly misidentify the connection between other bidders' actions and their private signals (Eyster and Rabin, 2005; Crawford and Iriberri, 2007; Eyster, 2019). Alternatively, subjects might have difficulties performing the type of contingent reasoning involved in equilibrium behavior. More precisely, in order to avoid overbidding, subjects should bid conditional on their private signal being the highest among all signals and should shave their bid downward. Anticipating the informational content of winning is, however, a difficult task. It requires a sophisticated level of contingent reasoning that, in general, most bidders struggle with. Besides common-value auctions difficulties related to contingent reasoning extend to other settings like "Acquiring-A-company" games (Bazer-

[1] Relatedly, overbidding in independent private value auctions has been attributed to misperception of winning probabilities (to some extent) (Dorsey and Razzolini, 2003), learning dynamics (feedback information) (Neugebauer and Selten, 2006), ambiguity aversion (Salo and Weber, 1995), anticipated loser's regret (Engelbrecht-Wiggans and Katok, 2007; Filiz-Ozbay and Ozbay, 2007), spite (Morgan et al., 2003), reference-dependent utility with induced values (Lange and Ratan, 2010) and imperfect best response combined with risk aversion (Goeree et al., 2002).

man and Samuelson, 1983; Charness and Levin, 2009; Martinez-Marquina et al., 2019, in an individual decision game variant), voting games (Esponda and Vespa, 2014) or asset markets (Carrillo and Palfrey, 2011; Ngangoue and Weizsacker, 2021). In all these settings, uncertainty appears to be a crucial factor in impeding contingent reasoning (Martinez-Marquina et al., 2019; Koch and Penczynski, 2018; Ngangoue and Weizsacker, 2021; Moser, 2019).

Note, however, that none of the behavioral explanations mentioned above hinge on a specific definition of uncertainty. Our findings are surprising since it had been assumed that the winner's curse was primarily the result of faulty strategic reasoning and not faulty Stage-1 valuations. This result could not be detected by previous auction studies because the two stages of the bidding process are typically not investigated separately as we do here.

Our study also connects to recent decision-theoretic experiments that have exposed the fragility of attitudes toward uncertainty. Subjects' attitudes have been found to vary with different sources of ambiguity (Abdellaoui et al., 2011; Li et al., 2018), with different sources of risk (Chew et al., 2012; Armantier and Treich, 2016) and sometimes with different outcomes (e.g., with money vs. time in Abdellaoui and Kemel, 2014). These treatments highlight that it matters how subjects think about uncertainty, and we contribute to this literature by proposing an additional treatment variation which puts the domain over which uncertainty is resolved in the foreground. In our study, the final outcome is always some amount of money, the mechanism generating uncertainty is similar (the source), but the object over which the uncertainty is defined varies. This matters substantially in our game with incomplete information because it implies that our subjects will have to form and update beliefs over different objects. This distinction is also picked up in a growing literature in economics and psychology on how people view lotteries with uncertain outcomes versus those with uncertain probabilities. The main findings appear to be that when asked to choose between lotteries involving uncertain outcomes or uncertain probabilities, subjects appear to have no strong preference (Kuhn and Budescu, 1996; Gonzalez-Vallejo et al., 1996; Du and Budescu, 2005; Eliaz and Ortoleva, 2016) while when asked to price these same lotteries subjects appear to value the uncertain outcome lotteries above those with uncertain probabilities (Schoemaker, 1991; Du and Budescu, 2005). The results of Experiments

II and IIIb are consistent with this existing literature on one-person decision problems, but our auction setting brings attention to the finding that these small differences observed in individual decision-making are substantially magnified in a strategic environment.

Finally, it is useful to point out that a number of things we do in this paper are novel to the experimental auction literature. For example, this paper is probably the first to separate the bidding process into two stages and investigate them separately. This separation leads us to elicit a number of objects typically not revealed in conventional experimental auctions such as a subject's estimate of the value of the object they are bidding on given their signal, their estimate of the value of the object in the event of having the highest signal amongst all competitors (something we elicit in Experiment III and that is needed to bid optimally), their beliefs about the highest bid they are likely to face in the auction given their signal, as well as their belief that they have the highest signal among all competitors, etc. All of these things are vital for understanding bidding behavior and we hope they will be useful to others.

The paper is divided in two main parts. In a first part (the following Section 2) we present the main Experiment I with its design, the theoretical hypotheses and the experimental results, which constitute our main puzzle. In the second half of the paper, Section 3, we tackle the puzzle by exploring potential explanations with the additional Experiments II to IV. We finally conclude with our interpretation of the findings in Section 4.

2 A Different Auction Game

2.1 The Main Experiment

A total of 361 students from New York University participated in the study.[2] The study consists of four experiments. Experiment I provides the main evidence on bidding behavior in auctions with 107 subjects. Experiment II with 105 subjects sheds some light on how, in a non-strategic setting, bidders value common-value versus common-probability objects. Experiments III and IV with 96 and 53 subjects, respectively, help us understand how subjects map their private signals into bids. In this section, however, we

[2]Participants were recruited with the software hroot (Bock et al., 2014).

focus on presenting the two main auction treatments CV and CP of Experiment I, and relegate the description of the Experiments II, III and IV to Section 3. All experiments were conducted in a between-subject design, in which subjects faced uncertainty either in values or probabilities.

In Experiment I 55 subjects were assigned to treatment CV and 52 to the other treatment CP. Sessions for the CV and CP treatments lasted approximately 90 minutes and subjects earned, on average, \$23.78. The currency used in the experiment were credits (₵) with ₵6 corresponding to \$1.

Both treatments had identical procedures. The experiment was computerized with oTree (Chen et al., 2016) and consisted of two parts. Subjects needed to pass a comprehension test before they could start the first part of the experiment. In the first part, subjects participated in a set of first-price auctions. In the second part, attitudes toward risk, compound risk and ambiguity were elicited (see Appendix C for a detailed description). At the end of the experiment, subjects learned their payoffs in the first and second parts and answered a small, unincentivized questionnaire. In the questionnaire, they provided some information on their socio-demographic background, about their general approach to the auction game, and took Frederick's cognitive reflection test (Frederick, 2005).

In the first part of both treatments, subjects engaged in 8 different auction environments with 10 separate auctions each. At the beginning of every auction, subjects were randomly placed into groups of four bidders ($i = 1, .., 4$). Subjects then bid for lotteries described as either common value (CV) or common probability (CP) lotteries. Both lotteries are defined by two parameters v and p where v is a non-zero payoff of the lottery and p is the percentage probability of receiving that payoff (with $(100 - p)$ defining the percentage probability of receiving 0).[3] In a CP lottery the two outcomes $\{v, 0\}$ are known but p is uncertain, while in a CV lottery, the opposite is true.[4]

[3]We deliberately focus on binary zero-outcome lotteries to keep the cognitive costs of computing expected values comparable.

[4]In auctions with affiliated values a prize in form of a lottery ticket may generate some precautionary bidding if subjects have decreasing absolute risk aversion (Eso and White, 2004; Kocher et al., 2015). In the instructions, we do not specifically frame the lottery as an *ex post* risk but subjects probably perceive it that way. The observed bids in our CV treatment are, if at all, too high and do not suggest that the lottery ticket introduced a precautionary premium by lowering bids, although the general direction of a corresponding

We define by k that aspect of the lottery that is known to the bidder (either $k =: p$ in the CV auction or $k =: v$ in the CP auction). Analogously, we define $\tilde{u}$ as the unknown component of the lottery, that is a random variable uniformly drawn from an interval $[\gamma_l, \gamma_h]$ with $0 < \gamma_l < \gamma_h < 100$, i.e., $\tilde{u} \sim U[\gamma_l, \gamma_h]$ (we use in the following tildes to denote random variables). Hence, in the CV lottery where p is known for sure, we define $\tilde{u} =: \tilde{v} \in [\gamma_l, \gamma_h]$ as the unknown aspect of the lottery while in CP, where v is known, $\tilde{u} = \tilde{p} \in [\gamma_l, \gamma_h]$ is unknown.

We will now describe the two main treatments in our experiment.

2.1.1 Common-Value Auctions

In a common-value auction subjects bid for CV lotteries that pay off either a positive value $\tilde{v}$ or zero credits. Subjects know p but have incomplete information about the positive value $\tilde{v} \sim U[\gamma_l, \gamma_h]$.

The computer determines the exact lottery by randomly drawing a value $\tilde{v}$. Subjects, however, do not observe this value at the moment of decision-making. Instead, each of the four bidders in the auction receives a private signal s_i independently from each other. The signal is informative about the true lottery in that it is drawn from an interval that is symmetric around the true value $\tilde{v}$. More precisely, $s_i \sim U[\tilde{v} - \varepsilon, \tilde{v} + \varepsilon]$, $\varepsilon > 0$. Signals become more informative with a smaller support, i.e., with decreasing ε.

A Bayesian bidder would infer from observing a specific signal s_i that the unknown value $\tilde{v}$ must lie within $[s_i - \varepsilon; s_i + \varepsilon]$. To help the subjects we provide this information to them before they bid. Given this information, subjects place a bid for the lottery at the bottom of the decision screen (see Figure 1 for an example).

At the end of an auction, the auction winner is determined and the true lottery value, v is revealed. The lottery is played, the winner receives the lottery's outcome, either 0 or v, and pays her bid. Except for their own profit calculation, the feedback is the same for all bidders: Every bidder observes the true lottery, the lottery outcome and the highest bid.[5]

DARA effect in common-value auctions is not clear. More importantly, if bids exhibit a precautionary premium, there are no apparent reasons for premia to drastically differ across treatments.

[5]The computer breaks ties between maximum bids randomly.

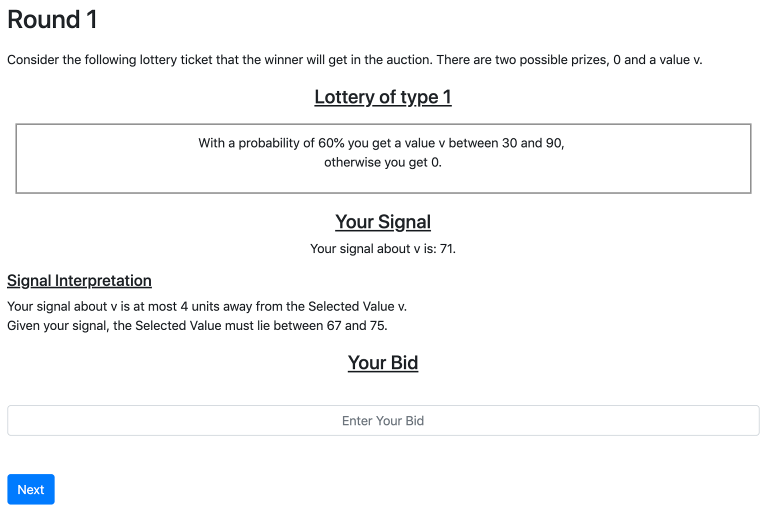


Figure 1: Example of Decision Screen in Treatment CV

2.1.2 Common-Probability Auctions

In a common-probability auction subjects bid for CP lotteries, that pay off a positive value v with a percentage probability $\tilde{p}$ and zero with the complementary probability $(100 - \tilde{p})$. Here, subjects know v (the known component of the auction) but have incomplete information about $\tilde{p}$, the probability of receiving v, where $\tilde{p} \sim U[\gamma_l, \gamma_h]$.

The computer determines the exact lottery by randomly drawing a probability $\tilde{p}$ and each of the four bidders receives independently from each other a private signal s_i. The signal is informative about the true probability in that it is drawn from an interval that is symmetric around $\tilde{p}$. More precisely, $s_i \sim U[\tilde{p} - \varepsilon, \tilde{p} + \varepsilon]$, $\varepsilon > 0$, implying that $\tilde{p}$ lies within $[s_i - \varepsilon; s_i + \varepsilon]$.

Subjects then place a bid for the lottery, whereupon the auction winner is determined and the true probability, p, is revealed. The lottery is played, the winner receives the lottery's outcome, either 0 or v, and pays her bid. Every bidder, here too, observes the true lottery, the lottery outcome and the highest bid.

2.1.3 Parameters

In both treatments subjects engage in 8 different auction environments and within each environment they participate in 10 auctions. The lotteries they bid for in each of the eight environments are defined by an n-tuple $(k, \bar{\gamma}, \varepsilon)$, where k is either the known probability p (presented to the subjects as a percentage) or the known value v in the CP auction, $\bar{\gamma}(= \frac{\gamma_l + \gamma_h}{2})$ identifies the interval $[\gamma_l, \gamma_h]$ (of fixed length) from which the uncertain component (either $\tilde{v}$ or $\tilde{p}$) is drawn, and ε defines the signal precision $(\frac{1}{3}\varepsilon^2)^{-1}$. With a 2x2x2 factorial design, we obtain 8 different parameter combinations by varying these 3 components across 2 sets of parameters: $k \in \{40, 60\}, \bar{\gamma} \in \{40, 60\}, \varepsilon \in \{4, 8\}$. Table 1 presents the 8 auction environments that our subjects engaged in in either the CP or the CV treatments:

Table 1: Lottery parameters

Lottery type	k	γ_l	γ_h	$\bar{\gamma}$	ε
1	60	30	90	60	4
2	40	10	70	40	4
3	40	30	90	60	4
4	60	10	70	40	4
5	60	30	90	60	8
6	40	10	70	40	8
7	40	30	90	60	8
8	60	10	70	40	8

Hence, the auctions presented to our subjects differ with respect to the known value k (column 2), the support of the unknown parameter $[\gamma_l, \gamma_h]$ (columns 3 and 4), as well as the signal precision given by ε (column 5).

In choosing our parameters we faced a set of constraints, the most important of which was to choose our values of k such that the CP and CV auctions were strategically equivalent. As one can see in Table 1, our design allows us to separately identify the sources of variation in our subjects' bid functions as we vary the different parameters of our auction in a ceteris paribus fashion. For example, we are able to hold the known parameter k (probability or value) constant and see how bids vary as we change the precision of the signal distribution or alternatively, the support, $[\gamma_l, \gamma_h]$, of the unknown parameter $\tilde{u}$. Detecting differences in subjects' bid functions as a result of these ceteris paribus changes, if they exist, allows us to infer how subjects process the different auctions they face.

Subjects then play 10 different auctions of each in these eight auction environments. For each of these 10 auctions, the computer randomly selects a true lottery on the basis of the environment's parameters. More precisely, the exact lottery (i.e., the true v of the CV or p of the CP lottery) and the corresponding signals could differ from auction to auction within an environment.

2.2 Predictions Under Linear Expected Utility

In this section, we discuss the standard benchmarks under risk-neutral expected utility to which we will compare the results.

The CV and the CP auctions are strategically equivalent under the assumption that bidders are risk-neutral expected utility maximizers. To make the analogy more salient, we will henceforth use the letters k and $\tilde{u}$. In the CV auction the probability is known ($k =: p$) but the value is unknown ($\tilde{v} =: \tilde{u}$), and vice-versa in the CP auction. To facilitate comparison between treatments we use percentage values for p and write the *ex-ante* expected payoff of the lottery as:

$$100 \cdot E[L] = k \cdot \bar{\gamma} \begin{cases} = p \cdot E(\tilde{v}) & \text{in CV,} \\ = v \cdot E(\tilde{p}) & \text{in CP,} \end{cases}$$

where $E(\tilde{v})$ and $E(\tilde{p})$ is the expected value of the $\tilde{v}$ and $\tilde{p}$, respectively.

There are three bidding functions to which we can compare empirical bids:

$$\texttt{Naive bid:} \qquad 100 \cdot E[L|s_i] = k \cdot s_i \tag{1a}$$

$$\texttt{Break-Even bid:} \quad 100 \cdot E[L|s_i = \max_{\forall j}\{s_j\}] = k \cdot \left(s_i - \varepsilon\frac{n-1}{n+1}\right),\ j = 1, ..., 4 \tag{1b}$$

$$\texttt{RNNE bid:} \qquad 100 \cdot b^*(s_i) = k \cdot \left[s_i - \varepsilon + \frac{2\varepsilon}{n+1} e^{-(\frac{n}{2\varepsilon})[s_i - (\gamma_l + \varepsilon)]}\right] \tag{1c}$$

A naive bidder will bid the expected payoff of the lottery given her private signal (see Equation 1a). A more sophisticated bidder will take into account the winner's curse effect and will bid the expected payoff assuming her signal is the highest. She will therefore shave her bid downwards to make, on average, zero profits with a break-even bid (see Equation 1b). A highly sophisticated bidder will shave her bid even more assuming that, in a risk-neutral Nash equilibrium (RNNE), every one else bids like her (see Equation 1c).[6]

Because predictions vary with parameters and signals, aggregate data will be mainly described with the measure of bid factors. Bid factors correspond to deviations from the naive bidding function and allow us to focus on statistics that are independent from the private signals. The theoretical bid factors with respect to RNNE (Naive bid - RNNE bid) and Break-Even bid (Naive bid - BE bid) are thus:

$$\texttt{Break-Even bid factor:} \qquad k \cdot \varepsilon \cdot \Big(\frac{n-1}{n+1}\Big) \tag{2}$$

$$\texttt{RNNE bid factor:} \qquad k \cdot \Big[\varepsilon - \frac{2\varepsilon}{n+1} e^{-(\frac{n}{2\varepsilon})[s_i - (\gamma_l + \varepsilon)]}\Big] \tag{3}$$

Thus, the computation of theoretical bid factors (with respect to both the break-even and the RNNE bid) is identical across the two auction formats, with the only difference being that in the CV auction $k = p$ (in percentage points) and in the CP auction $k = v$. Like in standard common-value auctions, bid factors depend mainly on the signal's precision (that is inversely related to ε) and the market size n.[7] The break-even and the RNNE bid do not differ by much; the analyses will therefore mainly focus on the naive and the RNNE benchmark as these represent the highest and the lowest bidding benchmark, respectively.

Despite the strategic equivalence of our two auction formats, we might very well suspect that behaviorally subjects treat them differently. Subjects may find it more difficult to process uncertain probabilities than uncertain values – a situation they face more frequently in their every day lives. Whether this difference leads to a difference in bidding behavior or a different incidence in the winner's curse across auction formats is something we

[6]The derivation of the symmetric risk-neutral Nash equilibrium can be found in Wilson (1977) and Milgrom and Weber (1982). Following standard experimental procedure (see e.g., Kagel and Levin, 2002), we constrain our attention to the signal domain ($\gamma_l + \varepsilon < s_i < \gamma_h - \varepsilon$) for which the risk-neutral Nash equilibrium (RNNE) bid function and the other benchmarks take the above functional forms.

[7]We chose $n = 4$ because in the experimental literature the winner's curse has been extensively studied in auctions with four bidders (see Kagel and Levin, 2002).

will let our data determine. We test two null behavioral hypotheses.

Hypothesis 1 *CV and CP auctions do not differ with respect to bids.*

Hypothesis 2 *There is no difference in the incidence of the winner's curse across our auction formats.*

Hypothesis 2, which focuses on the subsample of winning bids, can be valid even if Hypothesis 1 is rejected. In contrast to Hypothesis 1, however, Hypothesis 2 is not deduced from theoretical predictions but derives from the observation that none of the existing behavioral explanations for the winner's curse hinge on a particular definition of uncertainty.

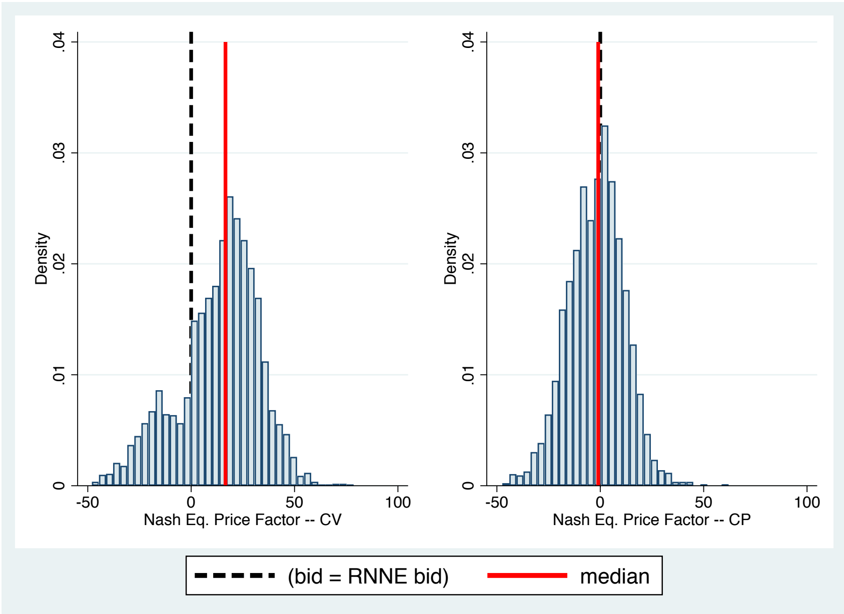
2.3 Results

In this section we investigate the two hypotheses stated above.[8] We first test whether the bidding behavior of subjects differ across our two auction formats (which it does) and then investigate whether this difference has a consequence for the incidence of the winner's curse.

Result 1 *Overall, bids significantly differ between the two auction formats: Subjects generally overbid in common-value but bid according to Nash equilibrium in common-probability auctions.*

Hypothesis 1 of identical bidding behavior across auction formats is clearly rejected. To study all auctions jointly, we consider bid factors that, for a better visualization, we define here as the difference between the subject's

[8]Despite passing the comprehension test, some subjects chose dominated bids that were above the highest possible outcome a lottery could pay off (given one's signal in CV or independent of the signal in CP). For subjects who made these dominated choices too frequently (more than 10% of all rounds) we interpret these choices as evidence of inattention and exclude 3 and 13 subjects in treatment CV and CP, respectively. In the other Experiments II to IV, we exclude in a similar manner 5 and 8 subjects in CV and CP, respectively. Our analyses, presents therefore the decisions of a reduced sample of 333 out of 361 subjects. It is important to note that, first, removing those subjects does not affect our main conclusion as we continue to observe a substantial difference in bidding behavior with the entire sample. Second, this reduced sample is balanced in the sense that across treatments the remaining subjects do not substantially differ with respect to demographics and personal characteristics measured at the end of the experiment (see Appendix Table A7.)



Note: Solid line corresponds to the median bid factor.

Figure 2: Bid Factors (=bid - RNNE bid) in Treatments CV (left) and CP (right)

bid and the Nash equilibrium bid.[9] Bid factors are then zero when subjects bid according to Nash equilibrium but are positive (negative) when they bid above (below) the Nash equilibrium bidding function. Figure 2 shows the distribution of bid factors. Bid factors are significantly different between the two treatments: They are predominantly positive in CV (indicating a fair amount of overbidding) but slightly negative albeit consistent with Nash equilibrium in CP. Appendix Table A1 gives a more detailed picture with the mean and median bid factors when the bid factor is computed not only with respect to the RNNE bid but also with respect to the break-even bid and the naive bid.[10] In CV, subjects bid more than the expected payoff of the lottery given their private signal. As mean and median bids are above the

[9]Empirical bid factors are usually defined as the difference between the naive bid and the subject's bid and reflect how much subjects shave their bid relative the naive expectations. We opted for a varying definition of bid factors that in our opinion offers a better visualization of the data. Here, bid factors are deviations from the Nash equilibrium bid, and bid factors equalling the theoretical Nash bid factor in Eq. (3) imply that our subjects submit naive bids.

[10]We focus here on the comparison of bid factors across treatments given that the empirical distributions of the randomly generated signals s_i were similar ($p = 0.113$ in Kolmogorov-Smirnov test).

naive bid, all three computations lead to, on average, positive bid factors. In CP, however, all three computations lead to, on average, negative bid factors because subjects bid slightly below the RNNE bid. In sum, subjects significantly overbid for CV lotteries, but bid close to Nash equilibrium for CP lotteries.

This difference between CV and CP occurs for all parameter combinations, i.e., for all eight lottery types. Appendix Figure A 3 shows the estimated median bid as a function of signals. In all eight auction types, the median bidding curves for CV lotteries lie substantially above while those for CP lotteries are slightly below the RNNE curve.

The question remains whether this difference in bid factors affects the incidence of the winner's curse. Figure 3 shows the distribution of bid factors in winning bids separately for the treatments CV and CP. Winners in both auctions fell prey to the winner's curse as average winning bids were significantly above the naive bid (see Appendix Table A2). Yet, the data reject Hypothesis 2: The difference in bid factors between the two auction formats remains substantial. Winners bid higher in CV and lost, on average, more than in CP (mean loss of ₵ -24.04 in CV vs. ₵ -10.04 in CP, p-value< 0.001 in t-test of differences with cluster-robust standard errors). As shown in Figure 4, the cumulative distribution function (CDF) of winning payoffs in CV auctions first-order stochastically dominates the CDF in CP auctions.

Result 2 *The winner's curse effect is attenuated in the common-probability compared to the common-value auction. Part of the reason is that the common-probability auction suffers less from adverse selection.*

While the winner's curse is less severe in CP than in CV, it is not clear whether this is because subjects reason better through the adverse selection problem with probabilistic uncertainty or because the adverse selection in CP is less severe in the first place. We first check whether the auctions provide the conditions for an adverse selection. The adverse selection is only present to the extent that the event of winning implies an increased likelihood of having the highest signal. To assess how informative winning is, we estimate the predicted probability of having the highest signal conditional on winning. We find that the adverse selection problem is present in CV, but marginal in CP. Winning in CV increases the likelihood of having the

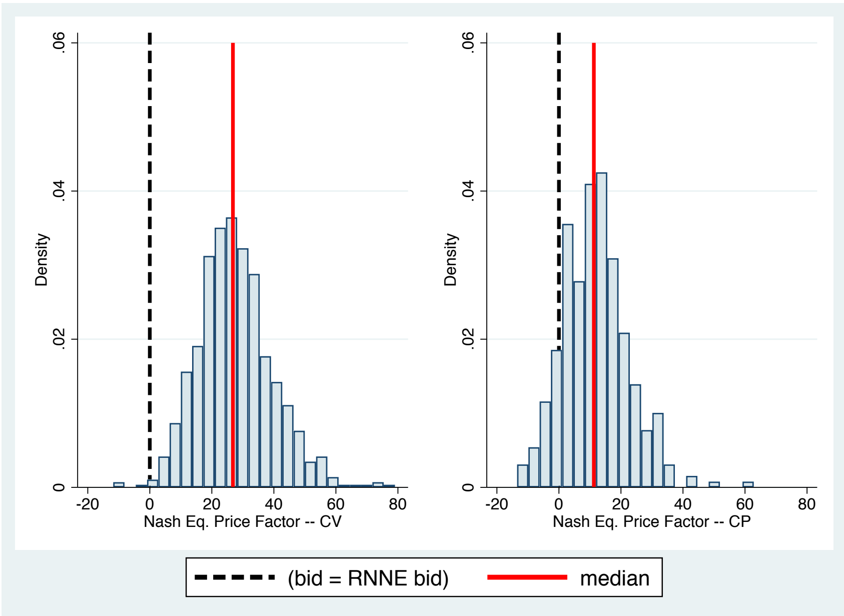


Figure 3: Bid Factors (=bid - RNNE bid) in Winning Bids in Treatments CV (left) and CP (right)

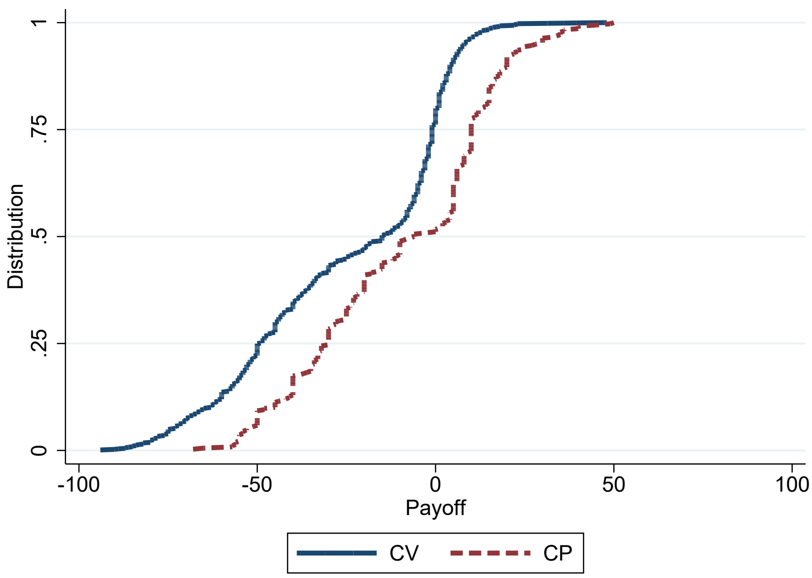


Figure 4: Cumulative Distribution Function of Winners' Payoff

highest signal from 19% to 36%, which is three times more than in CP (24% to 28%, as shown in Appendix Figure A 5).[11] This implies that, empirically, the CP requires bidders to shave less than the CV, which is the opposite of what we observe. Appendix Section B.2 provides a more detailed analysis of the adverse selection in those auctions. We conclude that, in the aggregate, the winner's curse is mitigated in CP because, there, the adverse selection problem is less severe. This is a first, aggregate indicator that subjects in CP may not be more sophisticated than those in CV, but it does not preclude the possibility that the ability to reason through the winner's curse differs at the individual level.

3 The Bidding Process and Its Constituents

3.1 Experiment II: Individual Non-Strategic Pricing

In this section, we investigate whether differences between our CP and CV auctions originate in the first stage of the bidding process in which subjects form subjective valuations for the good that is up for sale. In other words, did subjects bid differently simply because they resolved the fundamental uncertainty existing in Stage 1 differently without differing in their assessment of the strategic uncertainty they faced in Stage 2? A straightforward way to test this is to strip the auction game off of its strategic elements (cf. Charness et al., 2014, i.a.) by having subjects submit their willingness to pay (henceforth WTP) for the lotteries faced in our auctions without having them bid for them. This is what we do in Experiment II.

In treatment CVL we elicit subjects' WTP for a series of CV lotteries whereas in treatment CPL we do the same for CP lotteries. The WTP, rather than the certainty equivalent or the willingness to accept, serves here as the counterpart to a bid when a subject does not engage in any strategic reasoning. In a nutshell, treatments CVL and CPL provide an empirical benchmark for subjects' non-strategic naive bidding function, i.e., their bid as a function of a private signal when the latter is the only relevant information. At this point, it is worth mentioning that we view the naive bidding curve as the theoretic non-strategic benchmark. Yet, it could well be that,

[11] The probit estimation is done with the entire sample in Experiment I. The estimation with the reduced sample leads to more extreme results with a higher marginal effect of winning in CV, but a nonsignificant and weak effect in CP.

in the presence of others, other non-strategic considerations like competitiveness, thrill of winning, etc. induce naive bidders do bid differently than their individual valuations, leading to a discrepancy between bids and valuations that is not due to "strategic" reasoning in its strict sense. In the following we use the term "non-strategic" to refer to individual considerations, abstracting from any strategic and *non-strategic* effects arising from social interaction. The importance of this taxonomy will become clear in later subsections, when we compare our results in Experiments II and III.

There are many reasons why people might value CV lotteries differently from CP lotteries. One potential reason, which we focus on in Experiment II, is that each type of lottery presents a different way of compounding risk. More precisely, in the CV lottery the compounding is first over whether the good for sale has a positive value or not and then over its exact value while, in the probability lottery, the compounding is first over the exact probability of receiving the big prize and then, given this success probability, whether the lottery realizes to the big prize or zero. If subjects have different approaches to reducing these compound risks, this may affect the way they value the lotteries they are bidding for and, hence, be responsible for our auction results. We design Experiment II in a way that allows us to further disentangle this possibility.

The two treatments, CVL and CPL, share the same structure: each consists of three parts. In the part "Compound Lotteries" (CL) we investigate how subjects value lotteries in their ex ante and interim form (before and after receiving a signal about the lottery's worth) while in another part "Reduced Lotteries" (RL) we examine the impact of compounding risk by eliciting subjects' valuations for the reduced form of lotteries where the compounding is done for them. In the last part of the experiment we measure our subjects' attitudes toward risk, compound risk and ambiguity. This last part is identical to the last part of Experiment I (for a more detailed description see Appendix C). This last stage is also followed by a similar, unincentivized questionnaire.

Part CL: Valuation of Compound Lotteries Before and After Receiving a Signal. In our CVL and CPL treatments we elicited subjects' WTP for the lotteries with a Becker-DeGroot-Marschak mechanism (1964, henceforth BDM). Different subjects were recruited for the CVL and CPL treatments, but within each treatment subjects performed a variety of tasks. Hence, we have a between-subjects treatment with respect to whether the lottery had CV or CP features, but a within-subjects treatment with respect to the tasks each subject is asked to perform. Finally, it is important to point out that Experiment II is conducted outside of a competitive auction context – it is merely a willingness-to-pay exercise for a lottery. This fact will be important later when we examine the results of Experiment III.

In Part CL of the treatment, subjects engage in the same eight environments presented in the auction game. To isolate the effect of signal processing from ex ante evaluation, we separate the subject's valuation of a lottery type before and after receiving a signal. For example, in the treatment CPL a subject would be presented with a lottery with a fixed prize, say ₵60, and a probability p between 10% and 70% of getting that prize. With the complementary probability she receives zero. Given the specified range of possible probabilities the subject has to specify a WTP. We call this the *ex ante* WTP for the lottery since the subject is asked to state a WTP without any signal as to which probability might be the actual probability of receiving the big prize of ₵60.

To determine whether or not a lottery is bought we endow the subjects with ₵100 with which to bid, with any unspent credits paid to the subject. We then use the BDM mechanism so that after she submits her WTP, a random number between 0 and 100 sets the lottery price. The subject buys the lottery if its price is weakly less than her WTP. In that case, any gains or losses are added to or subtracted from her endowment of ₵100. Otherwise, she does not engage in the lottery and ends the round with her initial endowment. The experimental interface remains essentially the same as in Experiment I, with the only difference being that the subject submits WTPs for lotteries in a non-strategic setting rather than bids in an auction.

Subjects make 11 decisions in every environment. In a first round, they submit an *ex-ante* WTP without observing a signal. This round is followed by 10 rounds, in each of which a new lottery ticket is generated. For each of these 10 lottery tickets subjects submit a WTP *after* observing a signal. Since these rounds rely on signal processing, we refer to these decisions as interim WTP. Hence, in every environment of Part CL, subjects submit 11 decisions for 11 different lottery tickets: a first one without signal and 10 after receiving a signal for each of the 10 lottery tickets.

After every round with signal, the subject sees the actual lottery ticket, its price and its outcome irrespective of whether or not she buys. To keep learning dynamics as similar as possible to the auction treatments, there is no feedback after submission of the ex-ante WTP.

Part RL: Valuation of Reduced Lotteries. Part RL of the experiment focuses on subjects' ability to reduce compound lotteries. To identify whether cognitive difficulties are at work in our auction, we present subjects with the same lottery types but in reduced form. More precisely, we reduce the lotteries our subjects face by compounding the probabilities for them and present them with lotteries defined over final payoffs. In each round, a wheel is used to display the (up to 62) possible outcomes of a reduced lottery in a simple and condensed graph (see Appendix Figure A 1 for an example of a CV lottery). Similarly to Part CL, the subject sees her endowment of ₵ 100, the lottery wheel and then states her WTP in a BDM mechanism. In Part RL, we abstract from signal processing and present the subjects only with lotteries without signals to elicit their ex-ante WTP. Like in Part CL, the subject does not receive any feedback after submitting her ex-ante WTP.

A total of 104 subjects participated in the lottery treatments, of which 54 (50) were assigned to treatment CVL (CPL). We collected data across a total of nine sessions, where every session lasted approximately 90 minutes. We reversed the order of the first two parts CL and RL for one third of the subjects.

3.1.1 Results in Experiment II

To present our results we compute the analog to the bid factor in a non-strategic setting by measuring the difference between w_i, subject's willingness to pay for a lottery, and $E[L|s_i]$, the lottery's objective expected value given the subject's signal. To emphasize its correspondence to the bid factor, we call it the *non-strategic price factor* and denote it with $PF = w_i - E[L|s_i]$. In other words, the price factor is equivalent to the negative of a risk premium.

For a better comparison with the auction data, we use the fact that the $E[L|s_i]$ represents the naive bidding curve in the auction and compute the same measure with the bids, leading to a *non-strategic* bid factor (BF^{ns})

measure with respect to the naive benchmark ($BF^{ns} = \texttt{bid} - E[L|s_i]$). Figure 5a shows the distribution of non-strategic bid factors by treatment CV and CP. We juxtapose Figure 5b that shows the distribution of non-strategic price factors by treatment CVL and CPL. The treatment effect that we found in the auction experiment is largely attenuated in the non-strategic context. There is a small significant difference as subjects priced CV lotteries above, but CP lotteries below their expected value, willing to pay, on average, ₵4 more when the uncertainty was defined over values rather than probabilities (p-value < 0.001 in median test). This average difference of ₵4 (in the median, ₵6 in the means) is, however, substantially smaller than the difference of ₵17.4 observed in the auctions. While this suggests that strategic uncertainty seems to be a major amplifier of the main treatment effect, our later experiments modify this conclusion.[12,13]

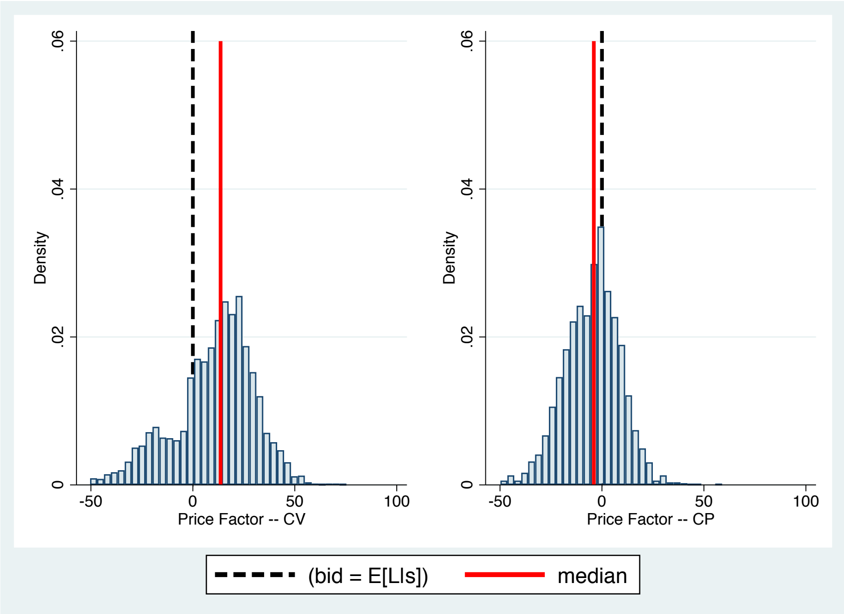
Appendix Section B.3 shows that subjects processed value and probability signals similarly. We also obtain a similar picture with the ex-ante valuation of CV and CP lotteries, for which we find no differences in median WTP (see Appendix Figure A 4). Without any further information in the form of a signal, subjects chose an average uncertainty premium of ₵4 regardless of whether uncertainty was represented by a range of values or a range of probabilities. In that sense, the general perception of lotteries with uncertain values versus uncertain probabilities does not explain differences in bids.

Remember, however, that the description of lotteries involves some understanding of compound risk. Since we find no difference in the values of lotteries ex ante, it is of interest to investigate whether their perception of lotteries is accurate in either case. To do this, we compare subject's valuations for the same lotteries in compound and reduced form.

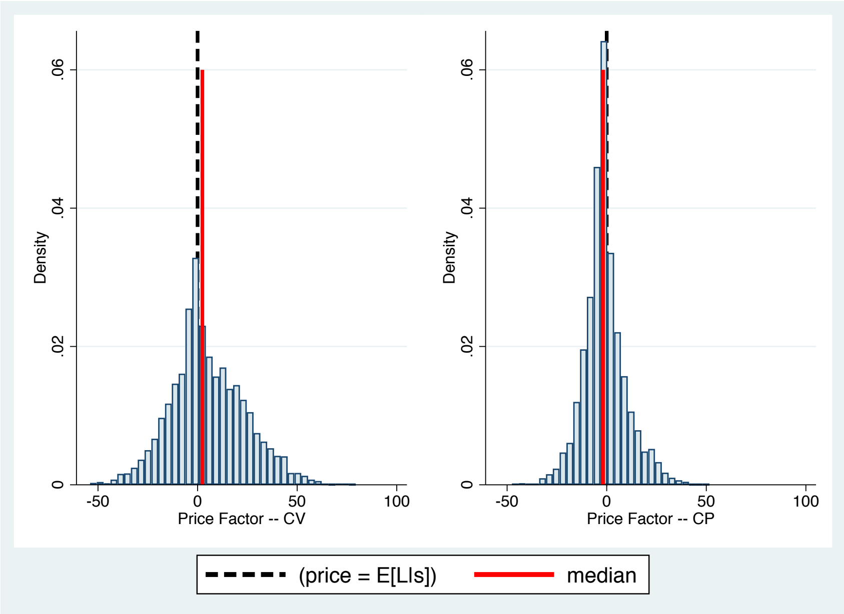
This within-subject comparison of WTP for otherwise identical com-

[12]This is consistent with the observation that the winner's curse is more prevalent with increasing number of bidders (Charness et al., 2014).

[13]Note that incentives differ between the auction and the lottery treatments. In first-price auctions, a Nash equilibrium bidder pays his bid and in expectations makes small profits. In the lottery treatment, subjects pay the random price, which is, in expectation and conditional on buying, half the subject's WTP. Monetary incentives are therefore, on average, higher in the lottery treatment and could partly explain the smaller differences in the lottery treatments. However, monetary incentives should have a similar effect across CV and CP treatments, but the asymmetry in findings between CV and CP treatments casts some doubts on monetary incentives being the main reason for the observed differences between auction and lottery treatments.



(a) Distribution of Strategic Bid Factors (=bid-$E[L|s_i]$) in the Auction Treatments CV (left) and CP (right)



(b) Distribution of Non-strategic Price Factors (=$w_i - E[L|s_i]$) in the Lottery Treatments CVL (left) and CPL (right)

Figure 5: Biding in Experiment I versus Pricing in Experiment II

pound and reduced lotteries reveals that, in the aggregate, subjects priced compound and reduced lotteries equally (see Figure 6). In CVL, subjects made no such distinction when valuing reduced and compound CV lotteries. The median premium for compound risk in values is zero, suggesting that compound risk in values may not necessarily have been perceived as such.[14] In CPL, they chose a small average compound risk premium of ₵ 2 for CP lotteries, pricing the reduced CP lotteries slightly higher than their compound analog.

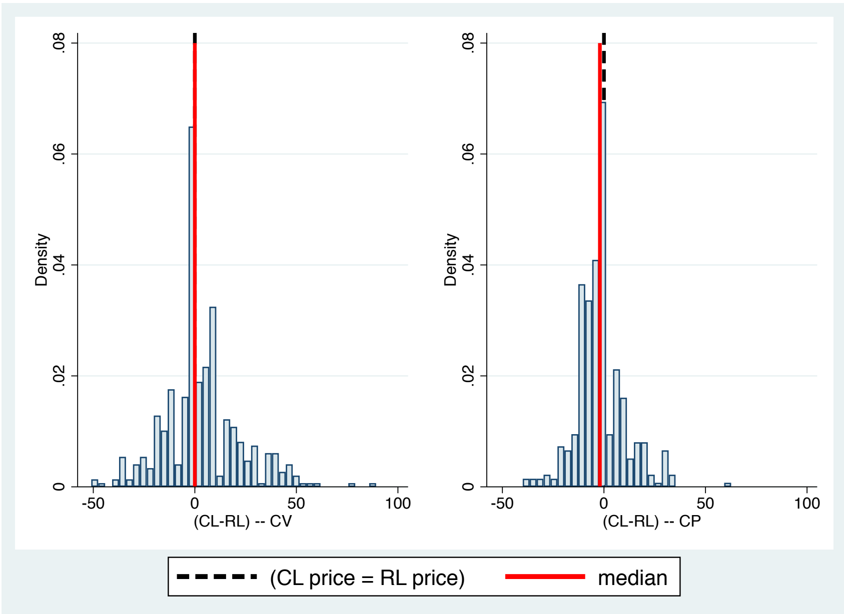


Figure 6: Differences Between Valuations for Compound and Reduced Lotteries ($=w_i^{CL} - w_i^{RL}$) in Treatments CVL (left) and CPL (right)

We next investigate the discrepancy between the auction and the pricing data. A comparison between strategic bids and non-strategic WTP for

[14]There are some order effects in the comparison of reduced and compound lotteries. Whether subjects first saw reduced or compound lotteries turns out to matter, albeit only in the CV treatments. In the aggregate subjects chose similar WTP with and without compound risk when they valued the compound lottery before its reduced form version (median compound risk premium of 0 in CV lotteries). Seeing the reduced lottery first, on the other hand, *increased* (rather than decreased) their WTP for the compound version of CV lotteries by ₵ 3.5. In other words, the median premium for compound risk defined over values is even negative, implying that the average subject was more averse to the reduced than to the compound version of the CV lottery.

the same lotteries reveals that strategic considerations have a different impact on bids depending on whether subjects evaluated CV or CP lotteries. Valuations for CP lotteries with and without strategic incentives are rather stable. On average, subjects priced CP lotteries almost ₵1.8 below their expected value, and in auctions, bid ₵2.21 less for the same CP lotteries ($p < 0.001$ in median comparison of bids and prices for CP lotteries). In contrast, valuations for CV lotteries substantially differed across settings. In CV auctions subjects bid, on average, ₵13 above the expected value of the lottery, but priced the same lotteries close to the expected value in the non-strategic environment (₵2 above expected value, i.e., on average ₵11 less than in auctions, $p < 0.001$ in median test).

Experiment II seems to suggest that the observed difference in bidder behavior across our CV and CP auctions was a Stage-2 phenomenon involving strategic reasoning given the way subjects resolved their fundamental uncertainty in Stage 1. This conclusion is premature however, since as we will see in Experiments III, IIIb, and IV that placing a subject in a competitive environment (as we do in these experiments) tends to change their Stage-1 valuations after they receive feedback in the auction.

3.2 Experiments III-IV: The Bidding Process in the Auction

In Experiment II we isolated Stage 1 by asking our subjects to price lotteries conditional on a single signal in a non-strategic setting. However, in equilibrium it is not enough to estimate the common-value item by only looking at one's own signal. One must consider that others have also received signals and, if they bid in a monotonic fashion, then a bidder must condition her estimate of the common-value item on her signal being the highest. The fact that there is persistent overbidding in our CV auctions suggests that, not only do subjects estimate the common-value item by considering more than their own signals, but they may even heavily weight the possibility of signals above their own as being relevant. Overestimating the item's value in the auction context (Stage 1) can lead to overbidding in the absence of faulty strategic reasoning in Stage 2.

Experiments I and II left the impression that strategic factors were responsible for the difference in behavior across CV and CP. Those experiments, however, only investigated the mapping from signals to bids and prices. In Experiments III and IV we look into the black box to identify what element in this mapping is different across our two auction formats. Technically, the ingredients of the black box should not depend on signals being over values or probabilities, yet our results from Experiments I and II suggest they do.

Our interest in Experiments III and IV is to determine whether there is a systematic difference across our two auction environments in the way our subjects either form estimates about fundamental values (henceforth fundamental estimates) or act strategically given a fixed fundamental estimate. Experiment III investigates the mapping from signals to fundamental estimates (Stage-1) *in a strategic setting*, while Experiment IV explores strategic (Stage-2) behavior.

3.2.1 Experimental Design

Procedures Experiments III and IV were conducted online on Zoom during the Spring and Fall of 2021. To make our experiments more efficient, we made use of the data in Experiment I. We matched every participant in the new experiments with three participants from auctions that took place in Experiment I. In other words, every new subject replaced one randomly chosen subject from an auction in Experiment I. The new subject then bid for the exact same lottery ticket, observed the same signal and bid against the same three opponents as the replaced subject from Experiment I. Hence, we held constant the environment our subjects faced by making it identical to that of Experiment I–except, of course, for the fact that they were bidding against subjects in a previous experiment, which subjects knew. This allowed us to collect more independent data since we did not need to recruit four subjects to obtain data on one auction. This also kept the feedback after each round as similar as possible because information about the winning bid changed only if a new participant won the auction.[15] As we will see below, this design replicated our results of Experiment I concerning the difference in bidding behavior across CVs and CPs.

[15]Virtual experimental sessions were conducted during the COVID19 pandemic. We also took into account the fact that it was less risky to conduct an online experiment as an individual decision making experiment rather than with groups (because of risks of losing group members due to internet connections or distractions). Each experiment had two parts with separate instructions to which subjects had access throughout the experiment. In addition, instructions were read aloud by the experimenter or made available through a video. In every experiment, a comprehension test before the beginning of Part I ensured that subjects understood the information structure and the auction (in Experiment III).

Experiment III As mentioned above, intelligent bidding in an auction requires the ability to estimate the expected payoff of a lottery given one's own signal and, in Nash equilibrium, the ability to estimate the lottery's expected payoff conditional on having the highest signal. The main objective of Experiment III was to shed some light on these Stage-1 tasks. We specifically wanted to know whether subjects form correct estimates of the lottery's worth in an auction setting (as opposed to a non-strategic setting as they did in Experiment II), in particular when they condition on having the highest signal and, more importantly, whether subjects performed these tasks differently across our value and probability auctions.

Experiment III consists of two parts. To assess how robust our results are when we match participants to previous subjects, in Part 1 we let our subjects bid for a lottery ticket after receiving a (value or probability) signal just as in Experiment I. In Experiment III, however, subjects participated in only 40 different auctions because of time constraints. More specifically, we used the same parameters as in Experiment I, but we focused on the parameter sets with $\epsilon = 4$, for which in Experiment I overbidding in CV was more pronounced. In Experiment III therefore, we have no variation in the signal's precision.

The second part of the experiment had 12 rounds, in which we elicited different estimates. Again, subjects were matched to participants from previous auctions and received a signal about the lottery. In each round, we elicited three objects in our value and probability auctions:

1. The Estimate Conditional on a Signal (that we call the Naive Estimate): Subjects stated their best estimate about the expected payoff of the lottery ticket given a signal. In the experiment we referred to the expected payoff as the true *average worth* of the lottery ticket. We described it as the payoff that they would get, on average, if the lottery ticket with its Selected Value or Selected Probability was played very often. There is one important difference between the estimate elicited here and the valuation stated in Experiment II: While in Experiment II we simply asked subjects to price the lottery given a signal in isolation, in Experiment III we elicited these values after subjects had participated in 40 rounds of auctions. In other words, their valuation task was not done in isolation, as was true in Experiment II, but in the context of an auction. This forced our subjects to take this auction

context into consideration when estimating the lottery's expected payoff. For example, the expected payoff of a lottery conditional on one solitary signal may strike subjects as different from the one conditional on knowing that the signal is just one of four and not necessarily the highest. If, for some reason, they thought that their signal might not have been the highest, they might have increased their estimates to incorporate this fact. This is, of course, false strategic reasoning since, to avoid the winner's curse, one should estimate the lottery's payoff under the assumption that one has the highest signal of all bidders.

2. The Estimate Conditional on Having the Highest Signal (that we call the Contingent Estimate): We also elicited subjects' estimates of the lottery's expected payoff in the hypothetical event of having the highest signal. Such contingent reasoning is required for bidding in Nash equilibrium. Differences between the Naive and the Contingent Estimate tell us whether subjects were able to construct Bayesian updates correctly, that is, whether they were able to compute correct fundamental estimates once they were nudged to consider the relevant conditional event of having the highest signal.

3. The belief about the likelihood of having the highest signal: We also asked subjects to assess the probability that the signal that they have received was the highest one among the four bidders' signals in an auction. This measure is necessary to interpret our data because someone who believes that she has the highest signal may not display any difference between her Naive and Contingent Estimate in the first place.

All point estimates were incentivized with a binarized scoring rule (Hossain and Okui, 2013).[16] In addition, we incentivized subjects to report the *smallest* interval for which they were certain that it contained the lottery's Expected Payoff Conditional on the Signal and its Expected Payoff Conditional on Having the Highest Signal (Schlag et al., 2015; Enke and Graeber,

[16] A bonus payment of ₵ 12 was paid if the estimate was sufficiently close to the object of interest. More precisely, the bonus was paid with probability Pr[(Estimate - object of interest)$^2 < K$] with $K \sim [0, 36^2]$. For the elicitation of probability beliefs a bonus of ₵ 24 was paid with probability Pr[($\mathbb{1}_{(s_i \geq s_{-i})}$) - guess)$^2 < K$] with $K \sim [0, 1]$, where $\mathbb{1}_{(s_i \geq s_{-i})}$ takes the value 1 if the subject had indeed the highest signal (and zero otherwise).

2021).[17] This measure is meant to reflect subjects' uncertainty about their estimates.

We also ran Experiment III in a slightly different variant, in which the two parts were swapped: While in Experiment III we elicited subjects' estimates about features of the lottery after subjects had already engaged in 40 auctions, in Experiment IIIb we elicited this information *before* they bid in auctions. Reversing the order of the two parts in Experiments III and IIIb allowed us to elicit fundamental estimates both outside and inside the auction context. More precisely, in Experiment IIIb, we told our subjects that their signal was part of a vector of four signals, but we did not reveal that lotteries would be auctioned off in the second part. Hence introducing Experiment IIIb controls for auction experience in the valuation of lotteries. The difference between Experiment II and IIIb was that subjects in Experiment IIIb knew that their signal was one of four signals drawn while in Experiment II they received a single signal in isolation.

Experiment IV In Experiment IV we direct subjects' attention to the Stage-2 task by providing them with sufficient Stage-1 information as to basically eliminate any fundamental uncertainty they may have. Our goal was to isolate strategic from fundamental uncertainty by providing our subjects with the most accurate fundamental estimate for Stage 1, leaving them with mainly strategic uncertainty. In Part 1 of the experiment, we explore subjects' strategic uncertainty by eliciting beliefs about their opponents' bids. Here subjects saw the same information as their peers in Experiment I, that is, a lottery ticket with an uncertain value or probability and then, based on their private signal, they stated what they thought the highest bid of the other three bidders was (we call it the Belief about the Competitive Bid). Again, subjects submitted first a point belief and then the smallest interval they were sure would contain the highest bid of the other three bidders. In this first part, subjects stated their beliefs for 20 independent auctions.

[17] To incentivize the choice of the interval, we penalized wider intervals with the following rule: subjects received a fixed bonus only if the object of interest was indeed in their chosen interval, but the magnitude of the bonus would depend on the interval width. The bonus was calculated as follows: $12 * [1 - (u - l)/(E[L(\gamma_h)] - E[L(\gamma_l)])]$ where l and u denote the chosen lower and upper threshold of the interval and $E[L(\gamma_l)]$ and $E[L(\gamma_h)]$ the minimum and maxinum expected payoff of the lottery. Thus, the smallest interval–i.e., a point prediction– would lead to a maximum bonus of ₵ 12, while increasing the interval width would decrease the bonus.

They did not receive any feedback between auctions so as to not bias their decisions in the subsequent Part II.

In Part 2, subjects engaged in the same auctions as in Part I. That is, they saw the same lottery tickets with the same signal. However, in this part we provided them with two pieces of information to allow them to weigh the fundamental and strategic risks they faced. The first one pertains to strategic uncertainty and reminds them of their belief about the competitive bid that they had stated for that particular auction in Part I (cf. box in the upper right corner of Figure A 2). The second one pertains to fundamental uncertainty. Here our goal was to reduce fundamental uncertainty as much as possible by telling our subjects that they had the highest signal among all four bidders. In addition, we explicitly told subjects what it meant to have the highest signal by telling them what the expected value or probability was given that their signal was highest as well as the resulting expected payoff of the lottery if one would multiply values with probabilities (see Appendix Figure A 2). Hence, they had all the information about the fundamental value of the auction they needed, leaving them only with strategic uncertainty about the opponent.[18]

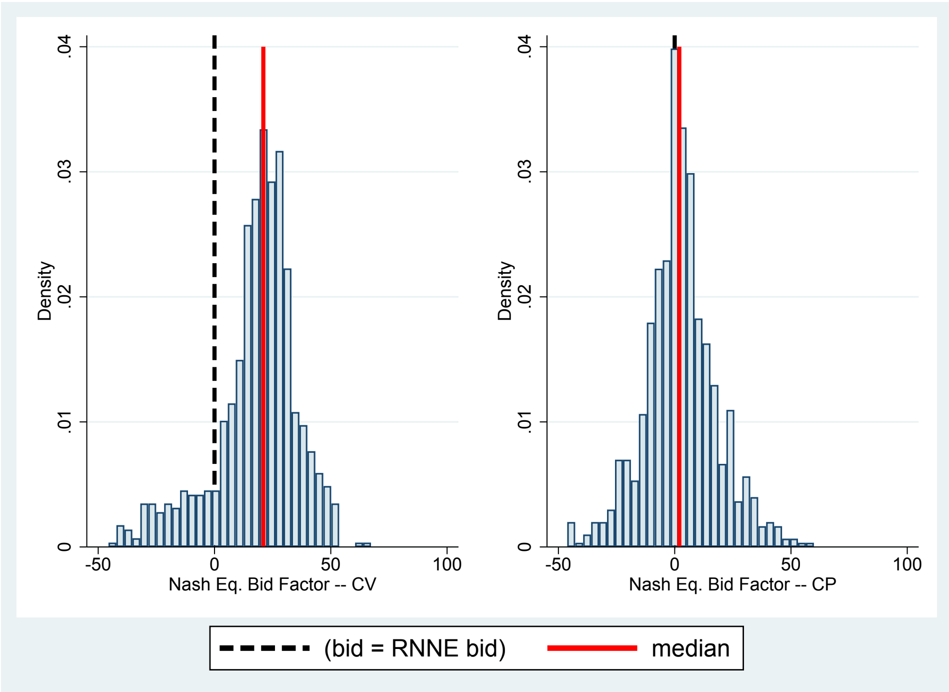
3.2.2 Results in Experiments III and IV

Stage 1 and Fundamental Uncertainty We start with Experiment III which investigates the tasks required in Stage 1 of the bidding process. Before getting into details, however, let us first check the robustness of our Experiment I results to our Experiment III design where subjects bid against previous Experiment I subjects.

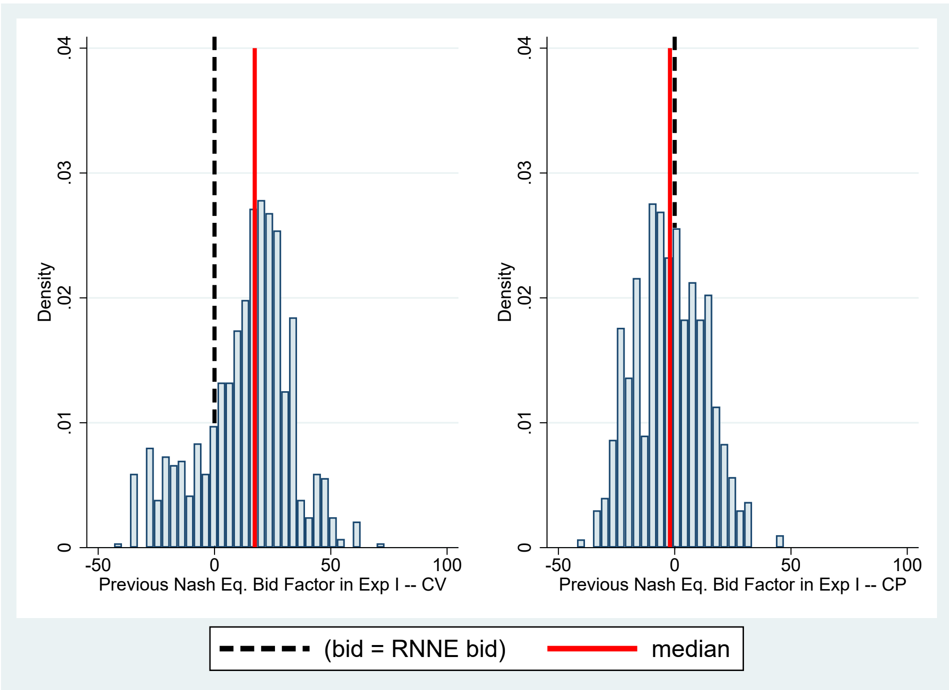
Result 3 *Subjects in Experiment III overbid in the CV auction compared to the CP auction–just as they did in Experiment I.*

This result is confirmed by Figures 7a and 7b. As in Experiment I, in

[18]It is of interest to point out that some of the information we collect in Experiments III and IV have, to our knowledge, not been collected in any previous auction studies, making our results here of relevance to auctions in general. While some previous studies have elicited estimates of the common-value item with or without incentives (Bazerman and Samuelson, 1983; Charness et al., 2019), and others have provided subjects with the opportunity to revise bids conditional on winning (Moser, 2019), to the best of our knowledge ours are the first experiments to directly elicit estimates about the common-value item contingent on having the highest signal, the probability of having the highest signal and beliefs about the most competitive bid.



(a) Bid factors in Experiment III



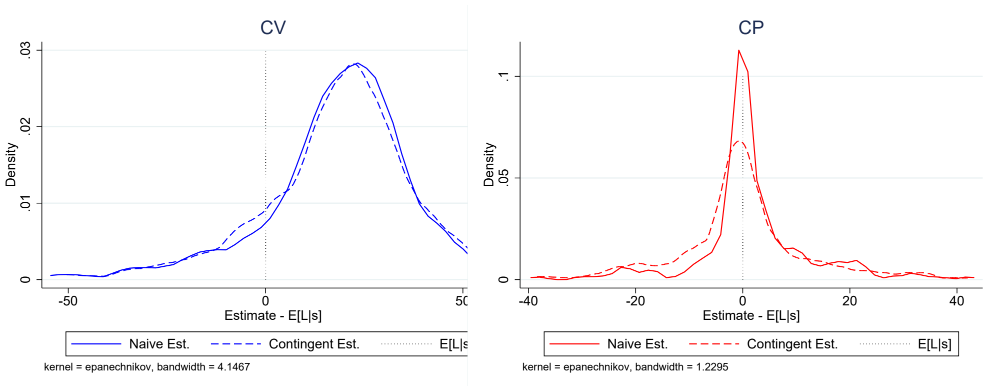
(b) Bid factors in Experiment I for identical signals

Figure 7: Comparing bids in Experiments III & I

Experiment III subjects in CV bid significantly more than their peers in CP. While in both auctions, subjects in Experiment III bid slightly higher than their peers in Experiment I, the difference in bids between CV and CP remains of similar magnitude: Subjects in CV bid, on average, ₵ 19.2 more than their peers in CP (compared to ₵ 17.60 for the same auctions in Experiment I). Hence, our results are robust to our design modification in Experiment III.

We next examine whether this differences in bids can be captured by different fundamental estimates in Stage 1 of the bidding process. The distributions of estimates are presented in Figures 8a and 8b, which plot the densities of estimates conditional on the signal (solid lines for Naive Estimates) and conditional on the signal being highest (dashed lines for Contingent Estimates) relative to the objective expected payoff $E[L|s]$ in CV and CP, respectively.

Result 4 *Subjects in CV overestimated the lottery's expected payoff conditional on the signal they received and also conditional on the signal being the highest amongst all bidders, while subjects in CP did not.*



(a) CV **(b)** CP

Figure 8: Naive and Contingent Estimates of the lottery's expected payoff in Experiment III

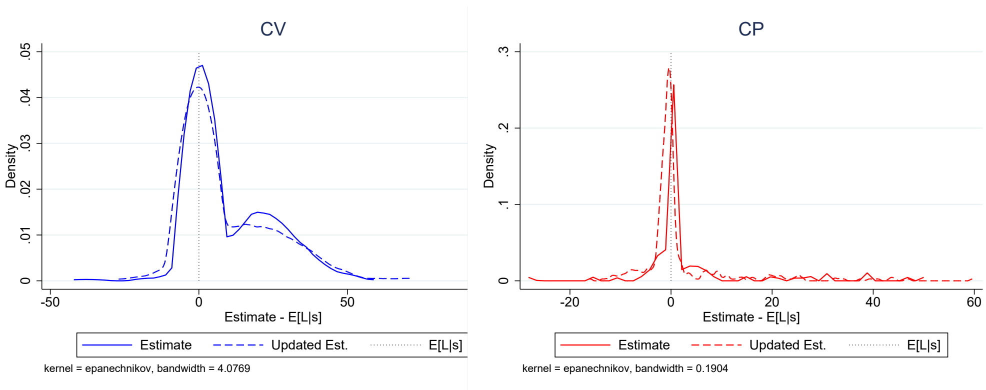
One striking feature in Figures 8a and 8b is that both Naive and Contingent Estimates of the lottery's expected payoff are significantly higher in CV than CP. In other words, for equivalent signals subjects believed that the lottery would, on average, pay more in the CV than in the CP. Furthermore, subjects did not condition correctly contingent on having the highest signal among the four bidders. The aggregate distribution of Naive and Contingent Estimates are practically identical. The same observation is made at the individual level where subjects in both CV and CP chose, on average, the same estimates in both tasks. This is significant because it indicates that subjects failed to do one of the most critical parts of Stage-1 processing, which is to condition correctly on their signal being the highest. If they had, the distribution of Contingent Estimates would have shifted to the left in both auctions, reflecting that having the highest of four signals lowers one's expectation about the lottery's payoff.[19] Thus, even when nudged to consider the right conditional event, subjects did not recognize that they needed to adjust their estimates downward.[20]

If you recall, when we asked subjects to value lotteries contingent on one signal in the decision problems of Experiment II, we found no difference in their valuations across the value and probability settings. The fact that they differ in Experiment III, where they had experience in the auction and knew that their signal was one of four received by bidders, is striking.

Note that in Experiment III subjects value lotteries after having experienced bidding in auctions. In Experiment IIIb however, we ask subjects to value lotteries before having such experience but knowing that the signal they received was one of four signals. The difference should be informative of the impact of experiencing competition on Stage-1 valuations. We find that the majority of subjects in Experiment IIIb estimated the lottery's worth close to its expected value (median difference of 0.4 in CV, $p = 0.76$, 0 in CP, $p = 1$, median regression with robust standard errors). In the CP

[19]We come to the same conclusion when we take into account subjects' probabilistic beliefs of having the highest signal. We find no systematic correlation between these probabilistic beliefs and the Naive (and Contingent) Estimates, which in turn may not be surprising given subjects' failure to adjust Contingent Estimates in the right direction.

[20]Note that this finding stands in contrast to Moser (2019) and Esponda and Vespa (2021) which differ in two ways. First, Moser (2019) and Esponda and Vespa (2021) study actions (bids) rather than fundamental estimates contingent on relevant events; Second, in their studies, the relevant event that subjects are nudged to consider is the event of winning. We believe that the two events, the event of winning and the event of having the highest signal, are not empirically equivalent. Conditional on winning, increasing the bid is a strictly dominated action, making it easy for subjects to recognize that bids can only be adjusted downward. However, in Nash equilibrium, the relevant informational event is the one of having the highest signal, thereby also allowing for the possibility of non-monotonic or asymmetric bidding. Conditional on having the highest signal, it may not be obvious to profit-maximizing subjects that estimates need to be adjusted downward. This is what we in fact find.



(a) CV

(b) CP

Figure 9: Naive and Contingent Estimates of the lottery's expected payoff in Experiment IIIb

variant of Experiment IIIb subjects continued to evaluate the lotteries at their expected value, albeit with a smaller noise. In CV, as can be seen in Figure 9a the density of estimates is shifted to the left compared to Figure 8a. While a small hump remains at higher values, the mode is centered around the expected payoff $E[L|s]$. This finding is consistent with the finding in Experiment II where subjects evaluated CV lotteries correctly in a non-competitive setting with one signal. Our findings here show that it does not matter whether signals are presented individually or as part of a vector as long as they are not placed in a competitive context.[21]

Stage 2 and Strategic Uncertainty When looking at bidding behavior in Experiment III we see that contingent on their estimate, subjects shaved their bid in a manner that was not significantly different across auctions.[22] This suggests that differences in bids do not stem from systematic differences

[21] We also note that in Experiment IIIb subjects formed better contingent estimates. In both treatment, subjects lowered their estimates by, on average, ₵1 ($p < 0.001$, median regression) contingent on having the highest signal (compared to a theoretical benchmark of ca. ₵1.7).

[22] In absolute numbers, subjects actually shaved their bids more in CV than in CP, but between auctions differences in shaving were nonsignificant. In CV, they bid, on average, ₵-2.20 below their estimates ($p = 0.131$, median regression). In CP, bids were, on average, ₵-0.8 ($p = 0.063$) below estimates. We obtain the same conclusion if we estimate the bid function as the function of endogenous fundamental estimates in a two-stage least squares procedure with mixed effects. The estimates of the bid functions are not significantly different across auctions.

in the way subjects convert their estimates into bids. Of course, we can only get a complete picture of how subjects translated their estimates into bids once we know their beliefs about their opponents' strategies. As you recall, in Experiment IV, we asked our subjects to predict the highest bid made by the three competitors they faced, which we call the Competitive Bid. This was the bid they would have to beat in order to win. The results are presented in Figure 10 where we place the objective expected payoff of the lottery given a signal, $E[L|s]$, on the horizontal axis and for each such expected payoff we plot two observed values: (i) the median belief about the competitive bid (black line) and (ii) the actual, median competitive bid (from Experiment I, gray line).

Result 5 *Subjects in CV expected their strongest competitor to bid highly and their expectations were correct. In contrast, subjects in CP expected their strongest competitor to bid close to the lottery's expected payoff, thereby underestimating the competition.*

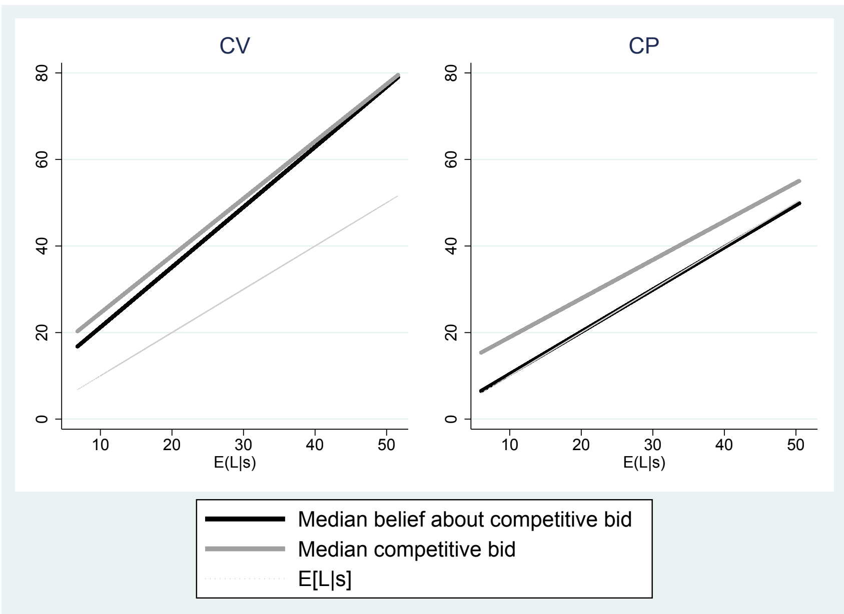


Figure 10: Beliefs and competitive bids

There are some intriguing aspects of Figure 10. First, beliefs about the competition one faces in the CV were significantly higher than those in the CP for a given expected payoff. This observation is consistent with the fact that equivalent signals induce higher fundamental estimates in CV compared to CP.[23] In addition , in the CV auction, subjects are approximately correct in terms of their beliefs about the median competitive bid of their opponents. Subjects expected high bids from their competitors (bids greatly higher than the expected payoff of the lottery) and these beliefs were confirmed. The pattern is different in CP. Here, subjects did not expect their competitors to bid above the expected payoff of the lottery, and actually underestimated the competition. These beliefs further sustain the difference in fundamental estimates observed in Experiment III. In CV, the fact that subjects believed their competitors bid close to their inflated estimates left them no room to shave. For the CP the situation is different in that subjects had lower estimates and also underestimated the competition.

It may not be surprising that in CV beliefs about the competitive bid were exceeding the lottery's expected payoff given that in Experiment III subjects had inflated estimates. A natural question that arises is whether subjects would adjust their bids downward if they had correct estimates. Both Experiments IIIb and IV, in which subjects had access to correct fundamental estimates before bidding, can be used to shed some light on this question. While in Experiment IIIb subjects computed correct fundamental beliefs themselves, in Experiment IV we provided them with these correct fundamental beliefs. If subjects in CV fail to form accurate estimates, then providing them with such information should change their bidding behavior. We in fact find this to be the case. We start by looking at the gentle nudge in Experiment IIIb. Figure 11 shows that having subjects enter the auction with correct fundamental estimates shifts the distribution of bids in Experiment IIIb to the left, relative to bids in Experiment III.

[23]This finding is akin to the type projection bias that induces one to believe that others have the same signal as one does (Breitmoser, 2019), although here subjects would be projecting their (biased) valuations rather than their type. Also note that there seems to be some endogeneity between valuations and beliefs about others as excessive valuations are only observed in the presence of others.

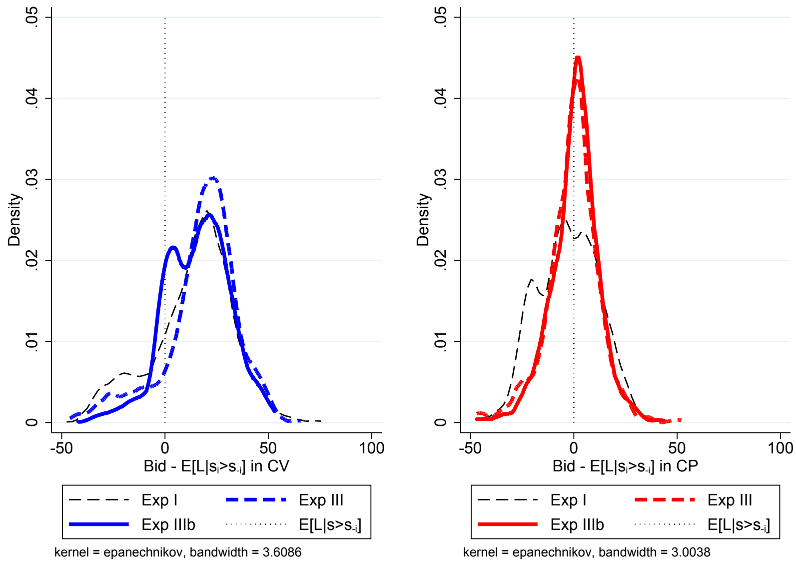


Figure 11: Bids in Experiments IIIb vs. I and III

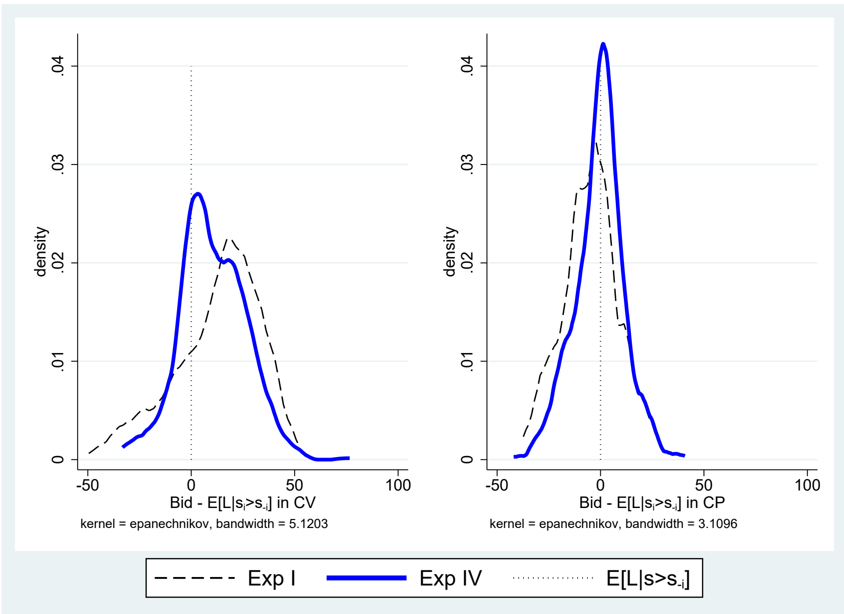


Figure 12: Bids in Experiment IV compared to Experiment I

The stronger nudge in Experiment IV leads to an even stronger shift. Figure 12 shows subjects' bids in Experiment IV as deviations from the expected payoff given that they were told their signal was the highest. We juxtapose the bids (relative to the same benchmark) of their peers in Experiment I who had the exact same signal but were not informed of its rank. As Figure 12 suggests, providing subjects with the conditional expected payoff had a correcting effect on bids in both auctions. In the CP, subjects adjusted their bids upward, around the conditional expectation. In CV, we observe that, relative to Experiment I, a substantial portion of bids was adjusted downward towards the conditional expectation, even if the correction was not enough to eliminate the aggregate evidence of overbidding. The shift to the left in the CV distribution is consistent with our conjecture that in both Experiments I and III, where subjects in the CV bid highly, a good part of this overbidding was the result of not computing proper valuations. When that processing was done by the experimenter, the result was a shift to the left in the distributions of bids in the CV. This confirms our suspicion that receiving a signal in the value domain led to the failure to process values correctly. When the expected payoff was provided, behavior changed, but could only do so partially as subjects' competitors from Experiment I who were not given this information did, in fact, bid excessively.

4 Discussion and Conclusion

This paper has presented a puzzle concerning the object of uncertainty in common value auctions. We found that when we auction off items with an uncertain common value, subjects largely overbid, but when the object of uncertainty is a probability, then average bidding is close to the Nash equilibrium.

In the process of investigating this puzzle our experimental design has shed light on how people bid in auctions generally by isolating and eliciting variables not typically seen in previous auction studies. For example, we have investigated this puzzle by breaking down the process of bidding into two stages. In Stage 1, given the signal received, subjects form an estimate of the item up for sale (either given their signal if they are naive or conditional on having received the highest signal if they are sophisticated). In Stage 2, they transform this estimate into a bid with the understanding that they will face other bidders. This two-stage process separates the fundamental uncertainty in the auction, how much the good they are bidding for is worth, from the strategic uncertainty, what will others bid given their signals.

To investigate which stage of the bidding process is responsible for the behavior we observed, we elicited some beliefs that have not been elicited before. For example, after receiving their signal in Treatment III, we asked our subjects to estimate some Stage-1 variables such as the value of the good they were bidding for both given their signal and also conditional on having the highest signal. This later estimate is, of course, crucial to avoid the winner's curse. We also elicited their view about the competition they faced (a Stage-2 variable) by asking them in Experiment IV for their estimate of the highest bid they expected to observe from other bidders. The elicitation of such subjective evaluations have rarely if ever been done in previous auction studies and offer a great opportunity to investigate the process that subjects go through in determining their bid.

Given this separation of the bidding process, there are several ways that our puzzle could be solved. For example, subjects could shave their bids identically across our CV and CP auctions but value the lotteries they face differently given identical signals. Here the difference in bidding would reside in Stage 1. Alternatively, subjects could value the goods identically across our two auction settings but bid differently in Stage 2 when facing strategic uncertainty. Finally we can have a combination of these explanations.

What we found was subtle. By and large the difference between bidding in our value and probability auctions resides in Stage 1. Subjects in the CV, who had experience in auctions, valued the item they were biding for higher than those in the CP and, as a result, bid more. This explanation places the focus on Stage 1 and the processing of fundamental uncertainty. It is worth noting that the bids close to the Nash equilibrium in CP were not driven by a more sophisticated reasoning through the winner's curse. In both auctions, subjects did not know how to interpret correctly the contingency of having the highest signal in a market. The differences in bidding originate rather in differences in subjects' estimates of the good.

The subtlety in our results comes from the fact that the discrepancy in valuations only occurs when subjects had experience in the auction. In other words, when subjects received a value or probability signal about the lottery outside of an auction setting, they did not only value the underlying lottery equally across our two domains, but valued it close to the item's objective expected payoff. These results were observed in Experiments II and IIIb. However, when subjects were presented with signals in an auction, or, more precisely, after having experience in an auction, (as was true in Experiment III) they overvalued the lottery in the CV but not in the CP. So there is an asymmetry in how bidders resolved fundamental uncertainty about values and probabilities but only when subjects were placed in a strategic setting. What this means is that the wall we have erected between assessing fundamental and strategic uncertainty is not as solid as we thought. There is a spillover.

One can only speculate about why Stage-1 valuations are more exaggerated with uncertain values. One possibility is that whenever the response mode (a ₵ bid) is aligned with the object of beliefs (a ₵ value), responses become more prone to biases (Tversky et al., 1988; Chapman and Johnson, 1994). Kagel and Levin have already alluded to the importance of the response mode to explain the difference between the high bids in sealed-bid auctions, in which prices must be submitted, and the lower bids in Dutch auctions with a binary accept/reject response mode.[24] While in Kagel and Levin's comparison the object of beliefs is the same (values) but the response mode differs (prices vs. accept/reject), in our experiments, the response mode is the same (prices), but the object of beliefs is different (values vs. probabilities). In CV, a bidder might fantasize about the highest prize she might be able to obtain, inducing her to bid higher without engaging in expectation-based reasoning, while in CP any fantasizing must occur over the probability of winning the high prize, inducing a bidder to take an expected value when converting her beliefs into a price. Note, the importance of expectation-based reasoning could only be detected because, in contrast to previous common-value auction experiments, in our design simply bidding one's signal does not conform with naive expectations.

[24]"The behavioral breakdown of the strategic equivalence of first-price and Dutch auctions and of second-price and English auctions is analogous to the preference reversal phenomenon, where theoretically equivalent ways of eliciting individual preferences do not produce the same preference ordering (see the Introduction, section III.F.l and Camerer, chapter 8, section 111.1).12. Psychologists attribute the preference reversal phenomenon to a breakdown in procedural invariance principles so that the weight attached to different dimensions of a problem varies systematically with the response mode employed. In the auctions, prices are higher when bidders must specify a price, as in the first and second-price auctions, compared to the open auctions where the decision is essentially to accept or reject the price that the auctioneer announces. Like the P(rice)-bets in the preference reversal phenomenon, the sealed bid auctions focus attention on the price dimension of the problem, and, like the P-bets, generates somewhat higher prices. On the other hand, the accept/reject decisions involved in the Dutch and English auctions focus attention on profitability, generating somewhat lower prices." Kagel (1995, p. 512)

The question is then why does this distinction only matter in the competitive setting? Research on motivated reasoning discusses how motives such as the desire to win can affect belief formation, in particular in environments where anticipatory utility may play a dominant role (Caplin and Leahy 2001; Benabou and Tirole 2002, i.a.; see Kunda 1990 for a review of experimental research). It may even lead to collective delusions in settings or markets where one's payoff is a function of others' actions as shown in Benabou (2013). In our CV auctions with binary lotteries it seems to be even more extreme because no information could rationalize subjects' excessive bids, suggesting that subjects are not only overoptimistic in their interpretation of information but also in their beliefs about the states of the world. In line with this, (Bar-Hillel and Budescu, 1995; Windschitl et al., 2010; Krizan and Windschitl, 2009) have noticed that outcome predictions are more prone to the desirability bias than likelihood judgments. Why this is true is not clear, but our findings corroborate this observed discrepancy in the literature and expose the importance of modeling the right object of uncertainty in settings that are prone to misjudgments.

As a complement to motivational beliefs, and to help explain why Stage-1 valuations rise in the CV when there is competition, our findings remind us of the economics of exclusion in Imas and Madarasz (2020), according to which other peoples' desire for a scarce object makes it more valuable to the decision maker. For example, competition could trigger a focus on the "best case scenario" for which it is worth "fighting", which, in the CV auction, means receiving the highest possible prize in the lottery. In contrast, in the CP exaggerating the probability of receiving the high prize offers less of an opportunity for wishful thinking (especially if there is probability weighting). Whatever the probability turns out to be, it must be multiplied by the prize to determine an expected value which is guaranteed to be less than the highest value hoped for in the CV auction.

To conclude, we think that this paper has taken us some distance in presenting a phenomenon that may be more general than the auction puzzle discussed here. Decision making involving distinct objects of uncertainty (value and probability) may differ in a wide variety of settings. For example, Lee et al. (2022) look at the preferences for temporal resolution of uncertainty across these same domains and find that subjects resolve uncertainty later when that uncertainty involves values as opposed to probabilities. Such a finding leads us to think that similar results can be found in other settings and that our paper is just a first step in exploring this phenomenon.

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A Experimental Interface

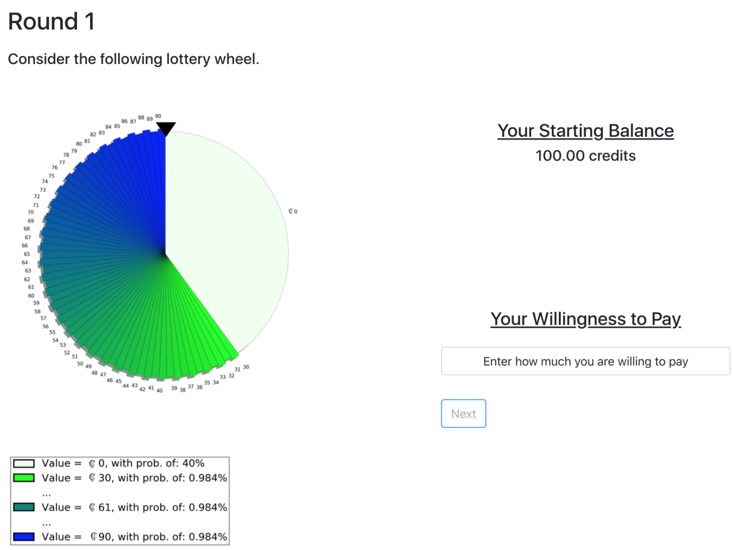

Figure A 1: Example for Screen Interface in Part RL

Figure A 1 shows the display of reduced CV lotteries in Experiment II. The display of reduced CP lottery was similar, but with only two possible outcomes.

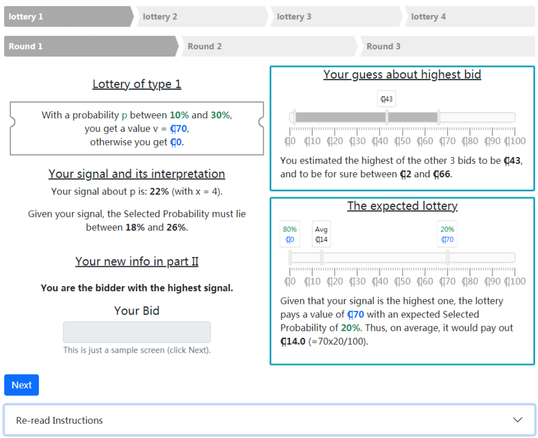

Figure A 2: Example of CP Interface in Part II of Experiment IV

Figure A 2 shows the interface in the second part of Experiment IV. The two framed boxes correspond to the two pieces of information given to the subjects. The upper right box reminds the subject of their belief about the competitive bid for the exact same lottery. The lower box renders information about the lottery to be expected conditional on having the highest signal in the market.

B Descriptive statistics

B.1 Bid and Price Factors

Table A1: Bid Factor (BF) for Reduced Sample

		Naive bid (bid-bid^{Naive})		Break-Even bid (bid-bid^{BE})		Nash-Eq. bid (bid-bid^{RNNE})	
		mean	median	mean	median	mean	median
Exp. I	CV	10.53***	13.6**	12.26**	15.32***	13.33***	16.45***
		(1.872)		(1.871)		(1.870)	
	CP	-4.60**	-3.80***	-2.84**	-2.04***	-1.77	-0.81**
		(1.424)		(1.425)		(1.423)	
	Diff.	15.13***	17.4***	15.11***	17.36***	15.10***	17.26***
		(2.346)		(2.345)		(2.345)	
Exp. III	CV	16.14***	19***	17.80***	21***	17.53***	20.60***
		(2.570)		(2.559)		(2.791)	
	CP	-1.33	-0.40	-0.64	1***	-0.31	0.80*
		(1.225)		(1.178)		(1.621)	
	Diff.	17.47***	19.4***	17.86***	20**	17.84***	19.80***
		(2.819)		(2.789)		(3.199)	
Exp. IIIb	CV	12.95***	13.2***	14.55***	15***	15.9***	16.9***
		(1.550)		(1.558)		(1.689)	
	CP	-0.60	0	1.23	1**	0.84	1.80***
		(1.099)		(1.141)		(1.380)	
	Diff.	13.54***	13.2***	13.32***	14***	15.07***	15***
		(1.885)		(1.941)		(2.166)	
Exp. IV	CV	9.46***	8.2***	10.66***	9.23***	11.45***	10.00***
		(1.828)		(1.828)		(1.828)	
	CP	-1.61**	-0.4	-0.41	0.76	0.39	1.60*
		(1.750)		(1.750)		(1.750)	
	Diff	11.07***	8.80***	11.07***	8.60***	11.07***	8.40***
		(2.522)		(2.522)		(2.521)	

Note: P-values: *: p-value<.1,**: p-value<.05, ***: p-value<.01. Robust standard error clustered by subject in parentheses. Clustering standard errors by sessions do not alter tests results and accounts for approximately 1% of the residual variance. In the remaining analyses standard errors are clustered at subject level.

Table A2: Bid Factor (BF) – Winning Bids in Exp. I

		CV	CP	Diff
Naive bid	mean	24.68***	9.50***	15.18***
(bid-bid^{Naive})		(0.914)	(1.107)	(1.436)
	median	23.40***	8.40***	15.00***
Break-Even bid	mean	26.41***	11.25**	15.17***
(bid-bid^{BE})		(0.917)	(1.109)	(1.439)
	median	25.16***	10.28***	14.88***
Nash-Eq. bid	mean	27.47***	12.33***	15.15***
(bid-bid^{RNNE})		(0.918)	(1.111)	(1.442)
	median	26.40***	11.52***	14.88***

Note: Cluster robust standard errors (CRSE) in parentheses.*: p-value<.1,**: p-value<.05, ***: p-value<.01.

Table A3: Price Factor in Exp. II

		CVL	CPL	Diff.
Part CL with signal				
Price Factor	mean	5.12***	-1.03	6.16***
($price - E[L\|s]$)		(1.676)	(1.006)	(1.945)
	median	2.4***	-1.8***	4.2***
Part CL without signal				
Price Factor	mean	0.75	-3.00**	3.75*
($price - E[L\|s]$)		(1.679)	(1.417)	(2.188)
	median	-4	-4	0
Part RL				
Price Factor	mean	-2.93*	-1.37	-1.56
($price - E[L\|s]$)		(1.684)	(1.132)	(2.022)
	median	-5	-1	-4***

Note: Cluster robust standard errors (CRSE) in parentheses. *: p-value<.1,**: p-value<.05, ***: p-value<.01.

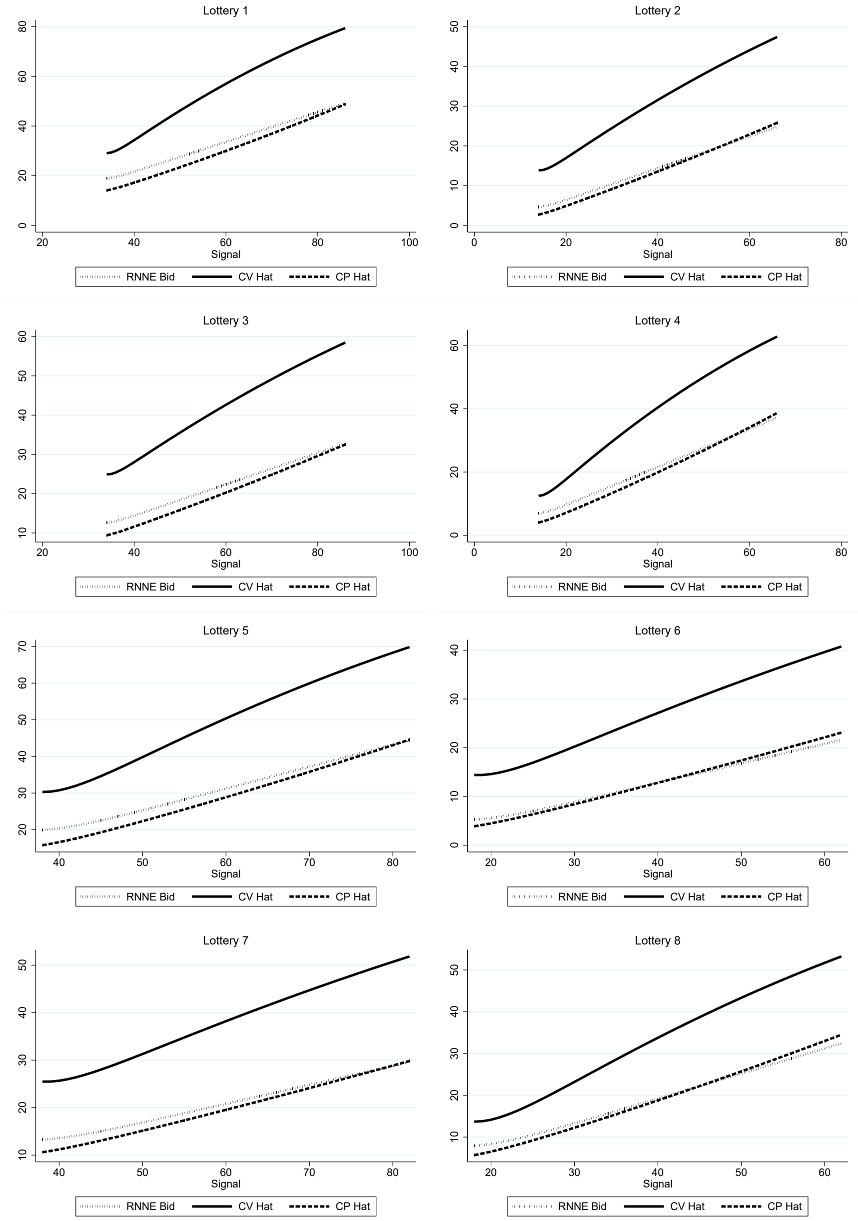

Figure A 3: Estimated Median Bids in CV and CP Auctions by Lottery Types (Experiment I)

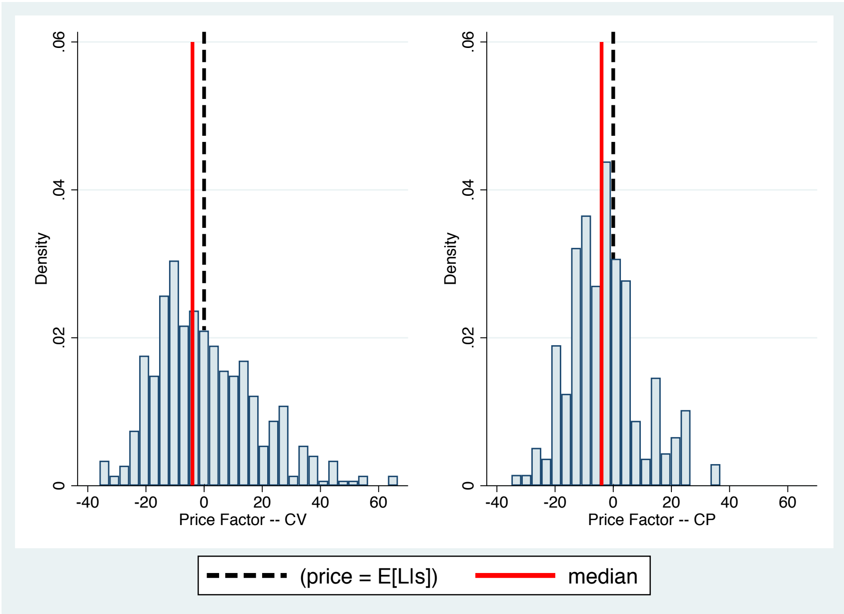

Figure A 4: Distribution of *Ex ante* Price Factors for Compound Lotteries (=$w^A - E[L]$) in Treatments CVL (left) and CPL (right)

B.2 Adverse Selection

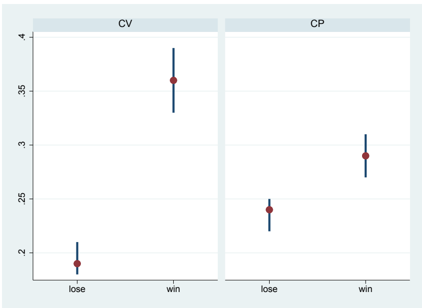

Figure A 5: Predicted probabilities of having the highest signal

While the winner's curse is less severe in CP than in CV, it is not clear whether this is because subjects reason better through the adverse selection problem with probabilistic uncertainty or because the adverse selection in CP is less severe in the first place. To shed more light on the extent of adverse selection, we juxtapose how informative two events are: the event of having the highest signal and the event of winning. The information contained in the event of having the highest signal tells us how much, in each auction, subjects must actually shave their bids to break even. This is the empirical benchmark for updating in a Bayesian manner. To this end, we regress the average lottery outcome on the signal and a dummy that takes the value one if the signal is the highest in the auction. The information contained in the event of winning, on the other hand, tells us how much subjects can actually learn from winning the auction. In a similar manner, we regress the average lottery outcome on the signal and a dummy that takes the value one if the bidder with the same signal won the auction. Note that the two events of having the highest signal and of winning will convey the same information if winning implies an increased likelihood of having the highest signal, thereby providing the conditions for adverse selection. We find that in the data having the highest signal in CV (CP) requires adjusting expectations by an average of ₵-3.08 (₵-2.65, $p < 0.001$ in either case) downward. In contrast, winning is not as informative, in particular in CP auctions. Winning an auction allows one to adjust expectations only by a fraction of what can actually be learned from having the highest signal: up to 35.71% in CV but only 10.07% in CP. Differences in the reduced sample are even more striking: 60.38% in CV versus 3.62% in CP. This is a direct result of a weaker correlation between signals and winning the auction. Appendix Figure A 5 plots the predicted probabilities of having the highest signal conditional on winning. The adverse selection problem is present in CV, but marginal in CP. Winning in CV increases the likelihood of having the highest signal from 19% to 36%, which is three times more than in CP (24% to 28%)[25]

B.3 Decision weights

[25]The probit estimation is done with the entire sample in Experiment I. The estimation with the reduced sample leads to more extreme results with a higher marginal effect of winning in CV, but a nonsignificant and weak effect in CP.

To assess the importance of signals relative to the known component of the lottery, we estimate the elasticity of the bid with respect to the known and the unknown (i.e., signal) component of the lottery. To this end, we use a simple Cobb-Douglas bidding function in the form of $b(s_i) = k^\alpha \cdot s^\beta$. A naive agent, for instance, would bid $E[L|s] = k^\alpha \cdot s^\beta$ with $\alpha = \beta = 1$.

Table A4: Median Regression Coefficients in Bidding

$ln(Bid)$	CV	CP	Diff.
$ln(k)$	$0.254^{*\dagger\dagger\dagger}$	$0.745^{***\dagger}$	-0.491^{**}
	(0.137)	(0.133)	(0.204)
$ln(s_i)$	$1.081^{***\dagger\dagger\dagger}$	$1.295^{***\dagger}$	-0.214
	(0.028)	(0.175)	(0.191)
Cons	-0.298^{**}	0.994^{**}	-1.293^{**}
	(0.137)	(0.496)	(0.627)
N	3260	2502	5762
Subjects	52	38	90
R^2	0.015	0.075	
$F-Test$	0.000	0.032	
MRS	$\approx 0.23\frac{s}{k}$	$\approx 0.57\frac{s}{k}$	

Note: Median regression with cluster robust standard errors (CRSE) at subject-level in parentheses. Significant difference from 0: *: p-value<.1,**: p-value<.05, ***: p-value<.01. Significant difference from 1: †: p-value<.1,††: p-value<.05, †††: p-value<.01. F-test refers to a test on equal weighting of known parameter and signal ($\alpha = \beta$).

We use the marginal rate of substitution (MRS) to compare the estimated bidding functions. The MRS represents here how much units of the signal subjects are willing to trade against a unit of the known parameter to maintain the same bid. For a naive bidder, the MRS equals $\frac{\alpha s}{\beta k} = \frac{s}{k}$. For our parameter variation, MRS under Nash equilibrium should be close to $\frac{s}{k}$. In both auction formats, the estimated MRS is smaller than $\frac{s}{k}$ ($\approx 0.23\frac{s}{k}$ in CV vs. $\approx 0.60\frac{s}{k}$ in CP in Appendix Table A4), indicating that subjects overweighted their private signal but underweighted the known component. Subjects in CV auctions put relatively more weight on the signal compared to those in CP auctions. Similar results are obtained with the pricing data, where MRS are closer to the naive benchmark $\frac{s}{k}$ (see Appendix Table A5). While subjects put more attention on signals in both CV and CP formats

Table A5: MEDIAN REGRESSION COEFFICIENTS IN PRICING

$ln(bid)$	CVL	CPL	Diff.
$ln(k)$	$0.546^{***\dagger\dagger\dagger}$	$0.810^{***\dagger\dagger\dagger}$	-0.264
	(0.157)	(0.056)	(0.067)
$ln(s_i)$	0.947^{***}	0.974^{***}	-0.027
	(0.069)	(0.044)	(0.066)
$Cons$	-2.500^{***}	-3.847^{***}	1.347
	(0.721)	(0.346)	
N	4256	4000	8256
$Subjects$	54	50	104
R^2	0.141	0.3919	
$F-Test$	0.0209	0.0017	
MRS	$\approx 0.57\frac{s}{k}$	$\approx 0.83\frac{s}{k}$	

Note: Median regression with cluster robust standard errors (CRSE) at subject-level in parentheses. Significant difference from 0: *: p-value<.1,**: p-value<.05, ***: p-value<.01. Significant difference from 1: †: p-value<.1,††: p-value<.05, †††: p-value<.01.

it is important to keep in mind that these signals are about different components of the lotteries. In CV treatments, subjects paid more attention to values in the lottery whereas in CP treatments they rather focused on the probabilities. In a nutshell, it appears that the uncertain component determines how subjects allocate their attention to different features of the auctioned item.

B.4 Information processing in Experiment II

We study the importance of information processing in the decision problem. The empirical value of a signal is obtained by comparing subjects' willingness to pay before and after receiving signal s_i. To this end, we regress subjects' willingness to pay w_i on objective measures like the prior expected value $E[L]$ and the information content of the signal given by $(E[L|s_i] - E[L])$. We also include a dummy D_{signal} that equals one when the willingness to pay was submitted after observing a signal.

As shown in Table A6, we do not find substantial differences in the way subjects processed these value and probability signals (like in Table A5).

Table A6: Median Regression Coefficients

WTP	EV	CV	CP	Diff
$E[L]$	1	0.898***†	0.830***†††	0.068
		(0.053)	(0.039)	(0.068)
$E[L\|s] - E[L]$	1	1.051***	0.905***†††	0.146
		(0.084)	(0.030)	(0.103)
D_{signal}	0	5.292***	2.074**	3.218
		(2.027)	(0.947)	(2.419)
$Cons$	0	-0.335	0.074	-0.409
		(2.349)	(1.497)	(2.783)
N		4256	4000	8256
$Subjects$		54	50	104
R^2		0.234	0.390	
$F - Test$		0.0434	0.0000	0.0000

Note: Median regression with cluster robust standard errors (CRSE) at subject-level in parentheses. Significant difference from 0: *: p-value<.1,**: p-value<.05, ***: p-value<.01. Significant difference from pricing at expected value (EV): †: p-value<.1,††: p-value<.05, †††: p-value<.01.

Under risk-neutral expected utility, pricing occurs at the expected value. That is, an increase of ₵1 in prior and interim beliefs is reflected in an equivalent increase of ₵1 in prices, while uncertainty premia (captured by the constant and the dummy variable) should be zero (cf. first column of Table A6). In treatment CVL, subjects reacted reasonably to variations in both, prior parameters and signals as the corresponding coefficients do not substantially differ from the RNEU benchmark. In treatment CPL, subjects slightly underreacted to variations in the parameters, but more importantly coefficients do not differ from the ones in CVL. Hence, subjects processed value and probability signals similarly.

Another striking observation is that in both CVL and CPL, the mere fact of observing a signal significantly increased WTP by ₵5 and ₵2, respectively. In other words, even when objective prior and interim expectations coincided, subjects were willing to pay more after observing a signal. This could be rationalized to some extent with a reduced uncertainty premium in interim beliefs, as seen in the treatment CPL where after getting a signal subjects bid closer to expected value. Rather surprising is that in CVL subjects bid, on average, even above expected values after seeing a signal, implying that the mere fact of getting a signal led subjects to move from an average positive to a negative uncertainty premium.

C Individual Covariates

C.1 Attitudes toward risk, compound risk and ambiguity

In the last part of the experiment, we elicited subjects attitudes toward risk, compound risk and ambiguity. Subjects started this part by first selecting the payoff relevant task. To this end they threw a dice, knowing that the number on top of the dice would define the selected task. The correspondence between the dice numbers and the tasks were, however, revealed only at the end of the experiment (Baillon et al., 2022). The exchange rate remained the same ($1 for 6 credits), but payoffs from the main part of the experiment were weighted more heavily than those in this last part (3:1).

This part consisted of only six decision problems. The six decision screens corresponded to three types of decision problems with two replicate measurements each.

C.2 Elicitation

We elicited risk attitudes with a multiple price list akin to Abdellaoui et al. (2011) and Gillen et al. (2019). Subjects faced virtual bags with red and blue chips. First subjects chose the color to bet on and then gave their certainty equivalent (henceforth CE) for their chosen bet. Risky bets were implemented with the following lottery (100:0.5;0) and (150:0.5;0) (i.e., a 50% chance of winning ₵100 / ₵150 or otherwise nothing).

To implement bets with compound risk, subjects were told that the computer would first select with equal probability one virtual bag from a set of virtual bags containing each a different mixture of red and blue balls (Figure A 6 shows an example of the screen for a bag with 20 chips), and would then randomly draw a chip from the selected bag. Subjects received ₵100 (₵150 in the replicate measurement) if the color of the drawn chip matched the color they bet on.

The implementation of ambiguous bets was similar, except that the mixture of red and blue chips was determined ex ante by a research affiliate and was not known to subjects.

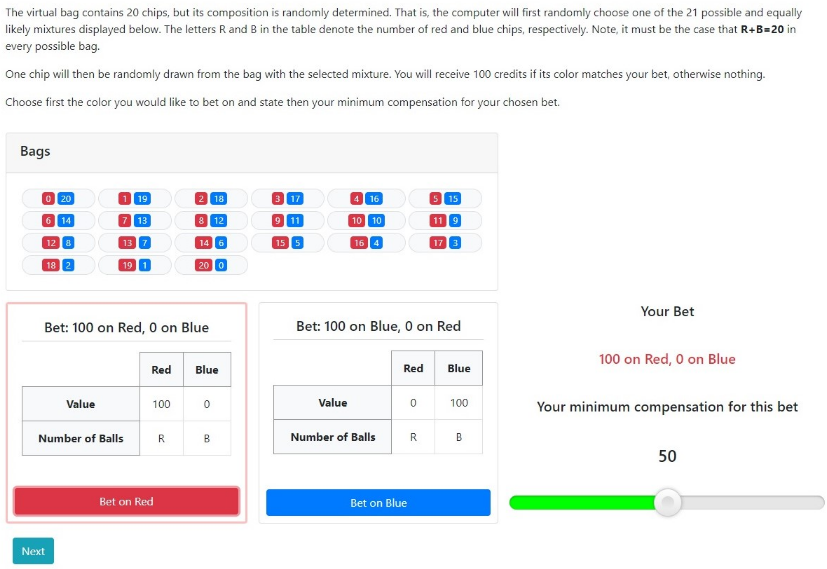

Figure A 6: Example for a decision screen to elicit attitudes toward compound risk (after selecting to bet on red and a certainty equivalent of 50 credits.)

C.3 Descriptive statistics

Methods. We classify attitudes as averse toward a type of uncertainty if subjects' prices display a premium for the corresponding lottery. In other words, we classify subjects as averse if they chose a CE that is smaller than the expected value. The subject's premium for a lottery is defined as the difference between its expected value and the subject's CE. A positive (negative) premium reflects aversion (proclivity).

We mitigate possible measurement error by taking the mean of the two replicate measurements: To this end we first normalize the CE by the lottery's expected value and average the normalized CE across the two replicate measurements.[26,27] Note that all decisions under uncertainty should be affected by a risk premium, if a subject is not risk-neutral. In a crude attempt

[26] For the ambiguous bets, we assume uniform beliefs over possible probabilities to compute the lotteries' expected value.

[27] Most subjects were also consistent in their attitudes, especially in their attitudes toward ambiguity. The redundant measures yield the same classification for 71.15%, 75.96% and 79.81% for attitudes toward risk, compound risk and ambiguity, respectively (in the full sample).

to control for risk attitudes in decisions with compound risk and ambiguity, we subtract the subject's average risk premium from the chosen premium for lotteries with compound risk and ambiguity (cf. Gillen et al., 2019). This yields a conservative measure for premia under compound risk and ambiguity since risk premia for binary lotteries should be highest when the success probability equals 50% (as in the risky lotteries). Thus, premia for compound risk and ambiguity that are corrected for individual risk premia become also negative in the cases where subjects were less averse toward compound risk/ ambiguity than toward risk (applies to 59 (60) out of 194 subjects for the compound risk (ambiguity) premium).

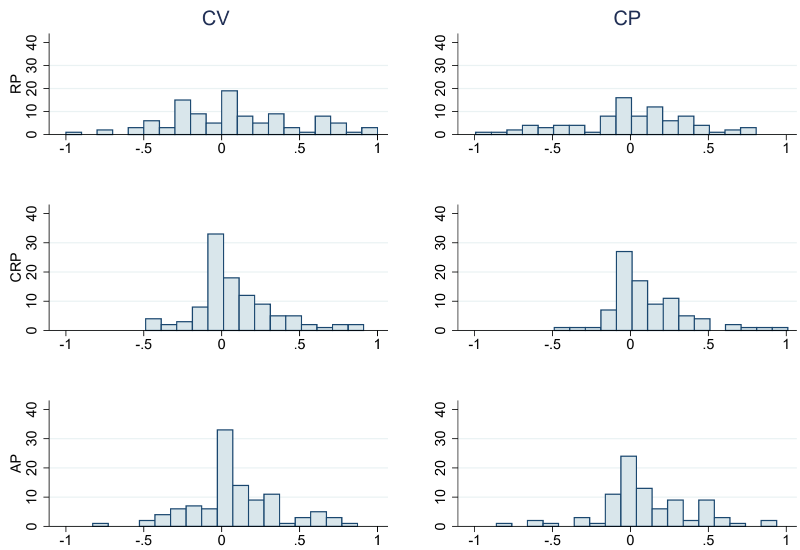

Figure A 7: Distribution of premia – by treatments CV (left) and CP (right).

Results. Figure A 7 shows the distribution of risk, compound risk and ambiguity premia, averaged across the two duplicate measures. Most subjects were averse.

Distributions of premia are not significantly different from each other across treatments (the Kolmogorov-Smirnov statistics yields p-values of $p = 0.21, p = 0.45, p = 0.89$ for risk, compound risk and ambiguity premia, respectively). Most subjects chose a premium close to zero, and attitudes toward compound risk and ambiguity are positively correlated (consistent with Halevy (2007)'s finding). The pairwise correlation coefficients are $\rho_{RC} = -0.24, \rho_{RA} = -0.10, \rho_{CA} = 0.54$.

C.4 Individual Characteristics

In general, individual characteristics do not significantly differ between the CV and CP treatments. The measures of the cognitive reflection tests (CRT) are higher in the treatments III-IV and have to be interpreted with caution because the experiment was conducted online.

Table A7: Means of Individual Characteristics by Treatment

		Male	Age	RP	CRT	CRP	AP
	CV	0.542	21.971	0.006	1.506	0.0966	0.123
		(0.069)	(0.378)	(0.054)	(0.145)	(0.036)	(0.040)
I	CP	0.613	22.359	-0.076	1.325	0.155	0.118
		(0.080)	(0.434)	(0.063)	(0.167)	(0.041)	(0.046)
	Diff	-0.070	-0.388	0.082	0.180	-0.058	0.005
		(0.106)	(0.577)	(0.083)	(0.221)	(0.055)	(0.061)
	CV	0.654	22.885	0.119	1.192	-0.001	0.004
		(0.098)	(0.553)	(0.096)	(0.246)	(0.054)	(0.066)
II	CP	0.522	22.174	0.195	1.478	0.039	-0.034
		(0.104)	(0.523)	(0.096)	(0.246)	(0.058)	(0.070)
	Diff	0.132	0.711	-0.076	-0.286	-0.040	0.038
		(0.143)	(0.763)	(0.140)	(0.359)	(0.079)	(0.097)
	CV	0.421	23.050	-0.028	2.300		
		(0.116)	(0.644)	(0.141)	(0.226)		
III	CP	0.389	23.278	0.069	2.500		
		(0.119)	(0.649)	(0.149)	(0.238)		
	Diff	0.032	-0.228	-0.097	-0.200		
		(0.166)	(0.936)	(0.205)	(0.328)		
	CV	0.522	21.913	0.068	2.391		
		(0.106)	(0.535)	(0.090)	(0.163)		
IIIB	CP	0.539	21.346	0.223	2.269		
		(0.100)	(0.503)	(0.085)	(0.153)		
	Diff	-0.017	0.567	-0.155	0.122		
		(0.146)	(0.735)	(0.123)	(0.223)		
	CV	0.429	23.276	-0.023	2.655		
		(0.094)	(0.572)	(0.153)	(0.160)		
IV	CP	0.333	22.286	0.141	2.048		
		(0.108)	(0.673)	(0.179)	(0.188)		
	Diff	0.095	0.990	-0.164	0.608^{**}		
		(0.143)	(0.883)	(0.236)	(0.246)		
	CV	0.545	22.426	0.037	1.739	0.059	0.076
		(0.047)	(0.254)	(0.044)	(0.099)	(0.031)	(0.036)
I-IV	CP	0.529	22.235	0.083	1.742	0.106	0.055
		(0.052)	(0.284)	(0.049)	(0.111)	(0.034)	(0.040)
	Diff	0.016	0.191	-0.046	-0.003	-0.047	0.022
		(0.070)	(0.381)	(0.066)	(0.148)	(0.046)	(0.054)

Note: *: p-value<.1, **: p-value<.05, ***: p-value<.01. Robust standard errors clustered by subject in parentheses.