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The nature of information and its effect on bidding behavior: Laboratory evidence in a first price common value auction☆

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ABSTRACT

We study in the laboratory a series of first price sealed bid auctions of a common value good. Bidders face three types of information: private information, public information and common uncertainty. Auctions are characterized by the relative size of these three information elements. Only half of our subjects bid differently depending on whether the last piece of information obtained is private or public but they do not react to each type of information as predicted by theory. The other half of the subjects do not distinguish between private and public information and either consistently underbid or consistently overbid.

1. Introduction

Common value auctions have been extensively studied in the laboratory. Two major findings are behavioral heterogeneity (Crawford and Iriberri, 2007) and the pervasiveness of the winner's curse (Kagel and Levin, 1986, 2008). Despite the existing literature, our knowledge of bidding behavior in those games is still incomplete. The goal of this paper is to improve such understanding. To this purpose we introduce two novel features in the design of an otherwise standard first price sealed bid common value auction with two bidders. First, we assume that the value of the good is the sum of N independent components and that each bidder observes the content of a subset of these components. Subjects always know which components are observed by the other bidder. Therefore, there are three clearly identified possible types of information in the game: private information (the components observed by only one bidder), public information (the components observed by both bidders) and common uncertainty (the components observed by no bidder). Second, we vary the number of components observed by each bidder, which affects the information structure in the auction. We consider five different structures: two with private information and common uncertainty, two with private information and public information, and one with private

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information only. Assuming risk neutrality, we show that the Nash Equilibrium (NE) bid in this auction is the sum of different elements each reflecting one type of information. With respect to private information, bidders shade their bids like in a typical common value auction (see e.g. Milgrom and Weber, 1982). With respect to common uncertainty and public information, bidders compete à la Bertrand and bid the expected value and the realized value respectively.

This auction is run in the laboratory and the experimental data is analyzed in different ways. First, we perform descriptive statistics of aggregate bids, aggregate payoffs, and changes in aggregate bids as we vary the information structure. We show that, on average, bidders do not distinguish correctly between the three different types of information. In our experiment, half of the subjects change their bids in a similar way whether the new piece of evidence is observed privately or observed also by the other bidder. This suggests that subjects do not make a rational strategic use of private information, resulting in deviations from NE predictions. Our aggregate analysis also reveals a large dispersion, implying a high level of behavioral heterogeneity in our population. To study this issue in more detail, we then conduct a cluster analysis. Since deviations from NE predictions seem to be driven by a wrong understanding of the information structure, we compute for each subject the average deviation from the NE prediction in each information structure. Given this new dataset, we conduct a model-based clustering method to endogenously determine clusters of individuals. This method reveals the existence of 6 distinct clusters in our population, differing in the size of their departures from NE as a function of the information structure. The analysis of each cluster separately reveals that heterogeneity across individuals is largely due to their different comprehension of the information structure. Only 63% of our subjects (clusters 1, 2 and 5) bid relatively close to equilibrium. Of these, 46% (clusters 1 and 2) realize the existence of the different types of information. They bid differently depending on whether the new information is private or public, although they still exhibit deviations from Nash: they overbid common uncertainty and underbid public information. The other 17% (cluster 5) have a much more imperfect grasp of the different types of information. Finally, 37% of the subjects (clusters 3, 4 and 6) hardly differentiate between public and private information and consistently overbid or consistently underbid.

Our analysis relates to two strands of the experimental literature: common value auctions and auctions with variable amounts of information. Kagel and Levin (1986) is the classical reference on common value auctions in the laboratory. They assume the value of the good is drawn from some distribution (typically uniform). Bidders receive a signal which is drawn from another distribution centered around the true realization. We use a slightly different model where the value of the good is the sum of several independent signals, and each signal may or may not be observed by bidders. This is formally closer to Albers and Harstad (1991), Avery and Kagel (1997), and Klemperer (1998).[1] As noted above, the novelty of our paper lies in explicitly modeling different types of information and varying their relative importance.

The experimental literature that varies the amount of information in auction settings is also related. Andreoni et al. (2007) study a series of private value auctions in which bidders know not only their own valuation but also the valuation of some other bidders. Naturally, the private value setting precludes any winner's curse problem. Mares and Shor (2008) analyze common value auctions with constant informational content but distributed among a varying number of bidders. The paper explores the trade-off competition vs. precision of estimates. Grosskopt et al. (2010) experimentally investigate the role of asymmetric information by varying the number of bidders who receive a signal about the common value of the good. Like our study, they find that the winner's curse increases with private information. However, they do not study how the existence of other types of information may affect the bidding strategy of subjects. Finally, in Brocas et al. (2014a) we study a similar problem than here using a second price auction and a slightly different design. The objective is to determine whether the imperfect differential treatment of private and public information also occurs under alternative mechanisms. The answer is affirmative: we also find that in second price auctions subjects differentiate insufficiently between private and public information. The paper however focuses on the study of individual strategies to explain the deviations from Nash equilibrium rather than a cluster analysis to understand common patterns of choice.

The paper proceeds as follows. The theoretical framework is briefly described in Section 2. The experimental setting is developed in Section 3. The aggregate analysis of the experimental data (aggregate bids, aggregate payoffs and changes in aggregate bids as a function of the type of information revealed) is discussed in Section 4. The cluster analysis and the regression analysis are performed in Section 5. Final conclusions are presented in Section 6. A sample copy of instructions can be found in the online Appendix.

2. Theoretical model

Consider a single good made of N components (with N even and greater than or equal to four). Each component $i \in \{1, \ldots, N\}$ has a value x_i independently drawn from a continuous distribution with positive density $g(x_i)$ on $[\underline{x}, \overline{x}]$ and cumulative distribution $G(x_i)$. The total value of the good is the same for every individual and equal to the sum of the components, $V = \sum_{i=1}^{N} x_i$.

[1] In the first study the good is the sum of the signals and each bidder observes only one signal, hence the number of bidders is equal to the number of signals. In the last two studies, each bidder has one private signal. The value of the good is the sum of the signals for one bidder and the sum of the signals plus a private value component for the other bidder. Therefore, when the private value component is zero, their model is equivalent to our treatment with only private information.

Two risk neutral bidders, A and B indexed by j, bid for this good in a first price sealed bid auction with no reserve price. Before placing their bids, A observes the first r components of the good, $\{x_1, \ldots, x_r\}$, and B observes the last r components of the good, $\{x_{N-r+1}, \ldots, x_N\}$, where $r \in \{1, \ldots, N-1\}$. Each bidder then observes exactly r components and does not observe exactly $N-r$ components. Each bidder also knows which components are and are not observed by the other bidder. Under this formalization, bidders always have *private information*: by construction, some components are only observed by A (e.g., x_1) while other components are only observed by B (e.g., x_N). It is useful to split the auction into three cases. When $r < N/2$, there is *common uncertainty* (on top of private information): the components $\{x_{r+1}, \ldots, x_{N-r}\}$ are not observed by any bidder. When $r > N/2$, there is *public information* (on top of private information): the components $\{x_{N-r+1}, \ldots, x_r\}$ are observed by both bidders. Finally, when $r = N/2$, there is neither common uncertainty nor public information, and the value of the good is the sum of the private information of both bidders. For the rest of the analysis we introduce the following notations.

- $X_A^r = \sum_{i=1}^{\min\{r,N-r\}} x_i$: the sum of A's private information.
- $X_B^r = \sum_{i=\max\{N-r+1,r+1\}}^{N} x_i$: the sum of B's private information.
- $E[X_\emptyset^r] = \sum_{i=r+1}^{N-r} E[x_i]$: the expected common uncertainty when $r < N/2$.
- $X_{\text{Pub}}^r = \sum_{i=N-r+1}^{r} x_i$: the sum of public information when $r > N/2$.

When $r \le N/2$, the private information of each bidder is an independent random variable with cumulative distribution $F^r(\cdot)$ and density $f^r(\cdot)$. When $r \ge N/2$, the private information of each bidder is an independent random variable with cumulative distribution $F^{N-r}(\cdot)$ and density $f^{N-r}(\cdot)$. Given that each component x_i has distribution $G(x_i)$ and components are independent, we have

$$F^r(X_A^r) = \int_{\underline{x}}^{\overline{x}} \cdots \int_{\underline{x}}^{\overline{x}} G(X_A^r - x_1 - \ldots - x_{r-1}) g(x_1) \ldots g(x_{r-1}) dx_1 \ldots dx_{r-1}.$$

and analogously for $F^r(X_B^r)$. Proposition 1 characterizes the optimal bidding strategies and equilibrium utilities in this auction as a function of r.

Proposition 1. *The unique symmetric equilibrium bidding function of agent j is:*

- $b^r(X_j^r) = E[X_\emptyset] + 2\left(X_j^r - \dfrac{\int_{\underline{X}^r}^{X_j^r} F^r(S)dS}{F^r(X_j^r)}\right)$ *when* $r < N/2$,
- $b^r(X_j^r) = 2\left(X_j^r - \dfrac{\int_{\underline{X}^r}^{X_j^r} F^r(S)dS}{F^r(X_j^r)}\right)$ *when* $r = N/2$,
- $b^r(X_j^r) = X_{\text{Pub}}^r + 2\left(X_j^r - \dfrac{\int_{\underline{X}^{N-r}}^{X_j^r} F^{N-r}(S)dS}{F^{N-r}(X_j^r)}\right)$ *when* $r > N/2$.

and the equilibrium expected utility of agent j is:

- $U_j^r(X_j^r) = \int_{\underline{X}^r}^{X_j^r} F^r(s)ds$ *when* $r \le N/2$,
- $U_j^r(X_j^r) = \int_{\underline{X}^{N-r}}^{X_j^r} F^{N-r}(s)ds$ *when* $r \ge N/2$.

Proof. We restrict the attention to monotonic bidding strategies that are differentiable. Assume that bidder B bids according to such a function and denote it by $b^r(X_B)$.

Let $r < N/2$. The expected utility of bidder A when he bids b_A^r is $U_A^r = Pr(b_A^r \ge b^r(X_B^r))\left(X_A^r + E[X_\emptyset^r] + E\left[X_B^r | b_A^r \ge b^r(X_B^r)\right] - b_A^r\right)$. Using the distribution of X_A^r, it can be rewritten as:

$$U_A^r = \left(X_A^r + E[X_\emptyset^r] - b_A^r\right) F^r(b^{r^{-1}}(b_A^r)) + \int_{\underline{X}^r}^{b^{r^{-1}}(b_A^r)} X_B^r f^r(X_B^r) dX_B^r$$

Maximizing U_A with respect to b_A^r and imposing the symmetry condition $b_A^r = b^r$, we get the following first-order condition:

$$\left(2X_A^r + E[X_\emptyset^r]\right) f^r(X_A^r) = F^r(X_A^r) b^{r\prime}(X_A^r) + b^r(X_A^r) f^r(X_A^r)$$

Integrating both sides yields the result. The ex-ante expected bid when $r < N/2$ is:

$$E[b^r] = \int_{\underline{X}^r}^{\overline{X}^r} \left(E[X_\emptyset^r] + 2\left(X_A^r - \frac{\int_{\underline{X}^r}^{X_A^r} F^r(s)ds}{F^r(X_A^r)} \right) \right) f^r(X_A^r)dX_A^r$$

Integrating the last term by parts, we get:

$$E[b^r] = E[X_\emptyset^r] + 2E[X_A^r] + 2\int_{\underline{X}^r}^{\overline{X}^r} \log(F^r(X_A^r))F^r(X_A^r)dX_A^r$$

$$\Leftrightarrow E[b^r] = E[V] + 2\int_{\underline{X}^r}^{\overline{X}^r} \log(F^r(X_A^r))F^r(X_A^r)dX_A^r$$

The ex-ante expected utility of bidder A is $E[U_A^r] = \int_{\underline{X}^r}^{\overline{X}^r} U_A^r(X_A^r)f^r(X_A^r)dX_A^r$ and at equilibrium $U_A^r(X_A^r) = \int_{\underline{X}^r}^{X_A^r} F^r(s)ds$. Integrating by parts, we get

$$E[U_A^r] = \int_{\underline{X}^r}^{\overline{X}^r} F^r(X_A^r)\left(1 - F^r(X_A^r)\right) dX_A^r$$

When $r = N/2$ there is no common uncertainty so we just need to remove the term $E[X_\emptyset^r]$. When $r > N/2$, We have a family of functions parameterized by X_{Pub}^r. Therefore, we can substitute $E[X_\emptyset^r]$ by X_{Pub}^r and follow the same procedure to get the result. □

The model is an extension of the “wallet game” to multiple signals. Albers and Harstad (1991) analyze the wallet game in a second price sealed bid auction with multiple bidders, each having exactly one signal and Klemperer (1998) discusses the effect of small asymmetries in a two-bidders English auction wallet game. In our model, the optimal bidding function is the sum of two elements. The first element reflects common uncertainty when $r < N/2$ and public information when $r > N/2$, while the second element reflects private information for all r. With regard to the first element, agents compete à la Bertrand and end up bidding the expected value of the common uncertainty or the realized value of the public information. With regard to the second element, agents trade-off the price vs. the likelihood of getting the good and they shade their bids as in the literature mentioned above. Our model is then a standard wallet game where we add a third wallet whose content is either observed by no bidder (common uncertainty) or by both bidders (public information).

It is crucial to note that the nature and the quantity of information that each agent possesses changes over rounds in a non-linear way. As we move from one round to the next, not only the support but the entire distribution function of the bidder's private information, $F^r(\cdot)$, changes. Because the distribution (and not just the realized values) affects the optimal bid, *it is not* possible to decompose the optimal bid in round $r+1$ into the optimal bid in round r plus a bid differential due to the revelation of x_{r+1}.

3. Experimental setting

We conducted 6 sessions with 8 or 10 subjects per session for a total of 52 subjects. The subjects were students at the California Institute of Technology who were recruited by email solicitation. All sessions were conducted at the Social Science Experimental Laboratory (SSEL). Interaction between subjects was computerized using an extension of the open source software package Multistage Games.[2] No subject participated in more than one session.

In each session, subjects made decisions over 15 paid matches, with each match being divided into 5 rounds. At the beginning of a match, subjects were randomly matched into pairs and randomly assigned a role as bidder A or bidder B. Pairs and roles remained fixed for the 5 rounds of a match. At the end of the match, subjects were randomly rematched into new pairs and they were reassigned new roles. All participants started the experiment with an endowment of 400 tokens.

The game closely followed the setting described in Section 2. Subjects in a pair had to bid in a first price sealed bid auction for a good made of $N = 6$ components. Each component $i \in \{1, \ldots, 6\}$ contained x_i tokens drawn from a uniform distribution in [0, 50] (so $G(x_i) = x_i/50$) although, to simplify computations, we restricted x_i to integer values, $\{0, 1, \ldots, 50\}$. The total value of the good was common to both bidders and equal to the sum of the six components. Visually, each component was represented by a box in the computer screen. The number of tokens inside each of the six boxes was drawn at the beginning of the match. Subjects could see the six boxes but not their content.

The match was then divided into 5 rounds. Round 1 corresponded to $r = 1$ in the theory section. Subject A observed x_1 (the content of box 1) and subject B observed x_6 (the content of box 6). Neither subject observed x_2 to x_5 (the content of boxes 2 to 5). Given this information, both participants submitted a bid for *the entire good* of value $V = \sum_{i=1}^{6} x_i$. Subjects could not

[2] Documentation and instructions for downloading the software can be found at http://multistage.ssel.caltech.edu.

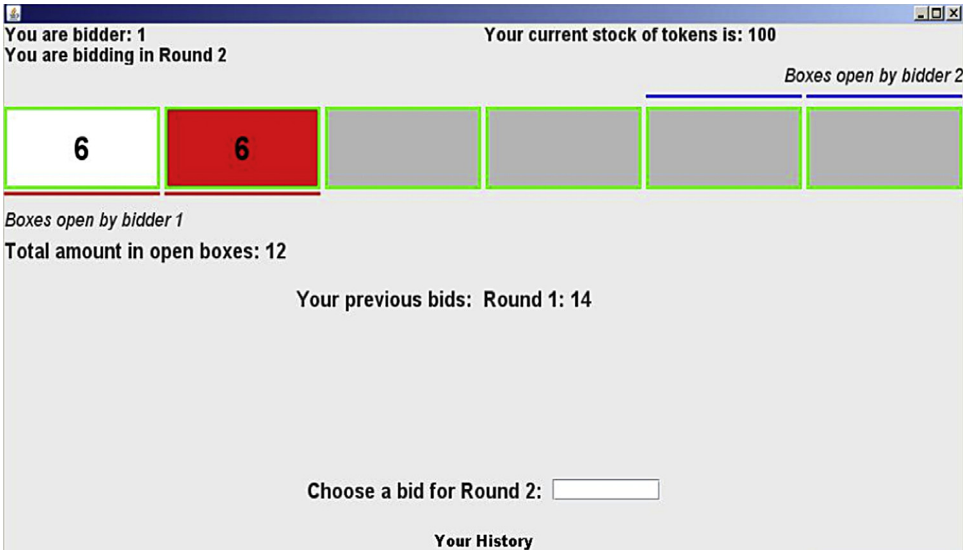

Fig. 1. Sample screenshot of user interface.

see the bid of the other subject, instead they moved to round 2, which corresponded to $r = 2$ in the theory section. Subjects A and B could now see the content of a second box (x_2 for A and x_5 for B), and placed a new bid again for the entire good V. This process continued until round 5 where A observed x_1 to x_5 and B observed x_2 to x_6. At the end of round 5, V and the five bids of each subject were displayed on the screen. One of the rounds was randomly selected by the computer, and subjects were paid according to the outcome of that round. Payoffs were computed according to the standard rules of a first price auction without reserve price: the highest bidder would get the item and pay his bid, while the lowest bidder would get nothing and pay nothing. A sample screenshot of the user interface in round $r = 2$ is presented in Fig. 1. It displays the subject's role, the current round, the stock of tokens, the content of the open boxes, a reminder of which boxes have been opened by the rival, and the subject's own bid(s) in the previous round(s) of that match.

Summing up, the only variable that changed between rounds was the amount of information each bidder had. By contrast, the opponent, role and total value of the item remained the same for the entire match. Naturally, it was crucial not to disclose the bids of the opponent between rounds since they contained information which could have been used as a signaling device, making the theoretical analysis substantially more intricate. The design is susceptible to anchoring effects due to the sequential revelation of information. Whether anchoring happened or not is an empirical question that the data analysis can answer (see Section 4.3).

The payoffs of each match were added or subtracted from the initial endowment. Participants could never bid more than their current stock of tokens, resulting in a potential selection effect due to liquidity constraints. However, this constraint was never binding in the experiment. Indeed, the stock of tokens of all participants was always greater than 300, the maximum value of the item and therefore the maximum possible bid.[3]

At the beginning of each session, instructions were read by the experimenter. The experimenter explained the rules and how to operate the computer interface. After the instruction period, one practice match was conducted for which subjects received no payment followed by an interactive computerized comprehension quiz that all subjects had to answer correctly before proceeding to the paid rounds (subjects who failed to answer the quiz correctly were coached individually until they could understand and answer all questions correctly). Then, the 52 subjects participated in 15 paid matches each of them divided into 5 rounds for a total of 75 bids per subject. Opponents, roles and values in all boxes were randomly reassigned at the beginning of each match and held constant between rounds of a match. In the end, subjects were paid, in cash, in private, their earnings, which were equal to their initial endowment plus the payoffs of all matches. The conversion rate was \$1.00 for 25 tokens, so each good was worth between \$0 and \$12. Sessions averaged one hour in length, and subjects earnings averaged \$27 including a \$5 show-up fee.

4. Aggregate analysis

The objective of this section is to test the predictions of Proposition 1 at the aggregate level. Table 1 presents the closed-form solutions of the bidding functions in all rounds for our particular case with 6 boxes and values drawn from a uniform distribution in [0, 50].

[3] We constrained the bids to be between 0 and 300: the minimum and maximum possible values of the good before any information is revealed.

Table 1
Bidding functions per round.

Round	Nash Equilibrium bid
1	$100+2\left(X_j^1-X_j^1/2\right)$
2	$50+2\left(X_j^2-X_j^2/3\right)$, if $X_j^2\le 50$
	$50+2\left(X_j^2-\frac{125000/3-2450-X_j^2+(X_j^2)^2-(X_j^2)^3/6}{2400+2X_j^2-(X_j^2)^2/2}\right)$, if $X_j^2>50$
3	$2\left(X_j^3-X_j^3/4\right)$, if $X_j^3\le 50$
	$2\left(X_j^3-\frac{720600+X_j^3/2-3(X_j^3)^2/4+(X_j^3)^3/2-(X_j^3)^4/12}{58825-3X_j^3/2+3(X_j^3)^2/2-(X_j^3)^3/3}\right)$, if $50<X_j^3\le 100$
	$2\left(X_j^3-\frac{93.75-7X_j^3/2+9(X_j^3)^2/4-(X_j^3)^3/2+(X_j^3)^4/24}{-175+9X_j^3/2-3(X_j^3)^2/2+(X_j^3)^3/6}\right)$, if $X_j^3>100$
4	$X_P+2\left(X_j^2-X_j^2/3\right)$, if $X_j^2\le 50$
	$X_P+2\left(X_j^2-\frac{125000/3-2450-X_j^2+(X_j^2)^2-(X_j^2)^3/6}{2400+2X_j^2-(X_j^2)^2/2}\right)$, if $X_j^2>50$
5	$X_P+2\left(X_j^1-X_j^1/2\right)$

4.1. Hypotheses

We first state the two main hypothesis we will be testing. Each corresponds to a prediction of Proposition 1.

Hypothesis 1. The average bid is U-shaped across rounds while the average payoff is hump-shaped across rounds.

Proposition 1 predicts that the expected NE bid $E[b^r]$ is symmetric and U-shaped across rounds: decreasing over rounds when $r \le N/2$ and increasing over rounds when $r \ge N/2$.[4] This is natural: since a Nash player always bids the realized amount of public information and the expected amount of common uncertainty, bid shading is increasing in the amount of private information only. Furthermore, if both bidders reduce their bids, their ex-ante expected utility increases since the ex-ante expected value of the good is constant. This means that the expected utility is hump-shaped across rounds: increasing over rounds when $r \le N/2$ and decreasing over rounds when $r \ge N/2$. Even if we observe deviations from Nash in the data, we expect these qualitative properties of bids and payoffs across rounds to hold.

Hypothesis 2. Bids depend not only on the amount of information but also on the type of information (private vs. public).

Proposition 1 predicts also that NE bids depend on both the quantity *and* the type of information. Sometimes, the last box revealed is a piece of private information (rounds 2 and 3) hence not observed by the other bidder. Other times, it is a piece of public information (rounds 4 and 5) observed by the other bidder as well. Again, even though we anticipate deviations from Nash, we still expect our subjects to treat these two types of information differently. In the next two sections we test these two predictions in our experimental data.

4.2. Aggregate bids and payoffs

We start with a general description of deviations in bids. Fig. 2 shows the difference between actual bids and NE predictions in each round. For each observation, we compute the NE bid and subtract it from the corresponding observation. The line in the middle is the median of this statistic, whereas the top and bottom lines are the 75th and 25th percentiles. The notches are the 95% confidence interval for the median.

Deviations from NE predictions exhibit a hump shaped pattern across rounds: increasing from round 1 to round 3 and decreasing from round 3 to round 5. Given private information increases from round 1 to round 3 and decreases afterwards, this result could in principle be explained by subjects falling prey of the winner's curse. However, such conclusion is misleading. Indeed, the median deviations in rounds r and $r+1$ are significantly different from each other at the 95% level for all r, and they are all significantly different from zero. More precisely, there is underbidding in round 1 and overbidding in rounds 2 to 5. The winner's curse hypothesis alone cannot account for this finding.

Also, the dispersion in the data decreases over rounds. Therefore, it is inversely related to the total amount of information (which increases over time). More precisely, decreasing common uncertainty (from rounds 1 to 3) or increasing public information (from rounds 3 to 5) reduces bid heterogeneity. These two findings taken together suggest that deviations from

[4] The result is true at the boundaries for any distribution ($E[b^0] > E[b^1]$ and $E[b^{N-1}] < E[b^N]$ for all $G(x_i)$). We conjecture that it should hold for all r when x_i is in a certain class of distributions but we have been unable to determine the properties of that class. Related problems have been analyzed by Shaked and Shanthikumar (1994), Bagnoli and Bergstrom (2005) and Mares and Shor (2008). Note, however, that in our setting both the support and the probability distribution function change from round to round, hence we cannot apply the results derived in these papers.

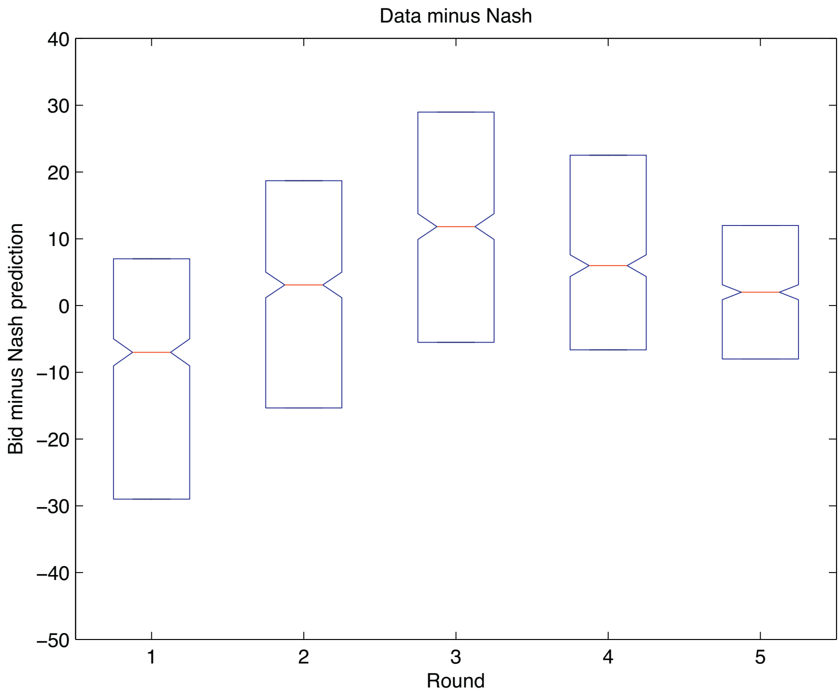

Fig. 2. Deviations from NE.

Table 2
Average bids.

Round	1	2	3	4	5
Mean data	109.41	113.52	116.70	120.90	127.40
	(1.28)	(1.22)	(1.22)	(1.25)	(1.40)
Mean NE	125.10***	115.39	106.85***	115.51***	128.16
	(0.51)	(0.81)	(1.06)	(1.12)	(1.20)
Mean BR	109.75	113.69	113.03***	111.79***	108.86***
	(0.51)	(0.61)	(0.78)	(0.80)	(0.98)

Standard errors in parenthesis.
*, **, ***: Significantly different from data at 90%, 95% and 98% confidence level (t-test.)

NE predictions cannot be entirely attributed to the winner's curse and are likely to be related to imperfect accounts of the different types of information. We will delay further discussions of this point to the next section.

These preliminary findings establish that bidding departs largely from NE predictions. Recall that Proposition 1 predicts that the average NE bid is U-shaped across rounds. To better understand the departures in our data, we construct Table 2 which displays the average actual bids per round (Data) and the equilibrium predictions (NE). For comparison, it also displays the average best response to the empirical distribution (BR). To construct this table, we compute the NE bid and the best response to the empirical distribution for each observation. Ideally, we would want to compute the empirical distribution of the bids for each possible value of private information and to calculate the expected gain of each possible bid for each possible value of private information. The best response to the empirical distribution would be the bid that maximizes the expected gain. However, this procedure would require a massive amount of data. Thus, we decided instead to divide the values of private information into 52 bins, each with 15 observations.[5] We used the average private information in each bin as the value of the opponent's private information in that bin. Then, we computed the best response to the empirical distribution using the method described above.

The average bid is increasing across rounds instead of U-shaped. Subjects become more confident in their information and bid more aggressively as their total information (whether it is private or public) increases. Note, however, that the difference between the average bid and the average NE prediction is relatively small in percentage terms (between 1% and 13%). Interestingly, the BR is hump-shaped across rounds, which is the opposite pattern of the NE predictions. Typically, it is optimal to underbid significantly in rounds 1 and 5 (bidding the NE implies winning with higher probability but very little

[5] In order to have the same precision when estimating the empirical distribution in each bin, we decided to have the same number of observations per bin. This implies that bins have different lengths.

Table 3
Average gains.

Round	1	2	3	4	5
Mean data	12.33	10.69	9.19	8.38	6.27
	(1.09)	(0.96)	(0.84)	(0.67)	(0.50)
Mean NE	10.03**	12.52*	14.95***	12.46***	8.50***
	(0.90)	(0.82)	(0.77)	(0.61)	(0.43)
Mean BR	17.40***	15.87***	12.76***	10.82***	6.04
	(1.10)	(0.96)	(0.81)	(0.69)	(0.51)

Standard errors in parenthesis.
* Significantly different from data at 90% confidence level (t-test).
** Significantly different from data at 95% confidence level (t-test).
*** Significantly different from data at 98% confidence level (t-test).

gain) and overbid in round 3 (to compensate for the rival's overbidding).[6] Subjects deviate more from the best response in late rounds, with a maximum difference of 17% in round 5.

We then perform a similar analysis of expected payoffs. Table 3 displays the average actual gains per round (Data), the equilibrium predictions (NE) and the gains obtained from best responding to the empirical distribution (BR).[7]

The average gain in our sample is decreasing over rounds instead of hump-shaped. This results from the fact that actual bids are increasing over rounds. Despite the small reported differences in bids, the percentage difference in gains is significant. By underbidding in round 1, subjects increase their payoff by 19% whereas by overbidding in rounds 2 to 5 they decrease their payoff between 15% and 38%. Moreover if subjects best responded to the empirical distribution their gains could have increased by as much as 50% in some rounds. We summarize the findings of this section in the following result.

Result 1. Hypothesis 1 is not supported by the data. Bids are increasing across rounds instead of U-shaped and gains are decreasing across rounds instead of hump-shaped. Overbidding in rounds 2 to 5 implies losses of up to 38%.

4.3. Aggregate bids and types of information

The previous section described the general patterns of bids across rounds and established the direction of departures from NE predictions. The objective of this section is to test the second implication of Proposition 1, namely that different types of information should be accounted for differently. This will allow us to relate departures to the treatment of the different types of information, which is the key novelty of our design.

The first natural question is whether subjects realize that the different types of information should be treated differently. For instance, in rounds 2 and 3 the last box revealed is a piece of private information whereas in rounds 4 and 5, the last box revealed is a piece of public information. Therefore, NE predicts that the change in bids from round 1 to 2 and from round 2 to 3 should be qualitatively different from the change in bids from round 3 to 4 and from round 4 to 5 (see Proposition 1, where $b^{r+1}(X_j^{r+1}) - b^r(X_j^r)$ depends on r). To see whether this is the case, we perform the following analysis.

In the absence of data constraints, we would like to analyze the change in bids as a function of the value of the boxes previously opened and the value of the new box, so as to better understand how subjects react to new information given their previous information. Due to the limited data available, we have to use an aggregate statistics. We organize the two variables somewhat arbitrarily into high values and low values. High values (H) correspond to cases in which the sum of the values in the boxes already opened (respectively the value in the new box) is above the expected amount of those boxes (respectively that box). Similarly, low values (L) correspond to cases in which the sum of the values in the boxes already opened (respectively the value in the new box) is below the expected amount of those boxes (respectively that box). We construct four groups 'H to H', 'H to L', 'L to H' and 'L to L' where the first letter refers to the value of the sum of opened boxes and the second to the value of the new box. For instance, 'H to L' means that the sum of the opened boxes is above expectation and the value in the new box is below expectation. For each of these four groups we calculate the average change in bids. Each column in Table 4 contains the average change in bids between rounds. For example, $r1 - r2$ refers to the change between rounds 1 and 2. For each group we report the NE predictions and the empirical data. Finally, the last two columns display a normal (nor) and non-parametric (non) test for the overall difference in means across rounds.

According to NE predictions, change in bids should be driven mostly by the new information. More importantly for our purposes, changes in bids from $r1$ to $r2$ and $r2$ to $r3$ should be vastly different from changes in bids from $r3$ to $r4$ and $r4$ to $r5$. Indeed, in the early rounds 2 and 3, the new box contains private information, which should be shaded. By contrast, in the late rounds 4 and 5, the new box contains public information, which should be entirely reflected in the bids. Therefore, when

[6] Round 5 is particularly interesting. Although the mean empirical bid coincides with the NE, the BR is still to underbid significantly. This is due to the *dispersion* in bids: by underbidding, subjects decrease the probability of winning the item but increase substantially the net gain in case of success.

[7] Remember that we only paid subjects for one randomly drawn round per match. However, when we mention 'gain' we refer to the profits subjects would have made had they been paid for that round. NE gains were computed as if all subjects in the population were bidding the NE.

Table 4
Average change in bids over rounds.

		$r1-r2$	$r2-r3$	$r3-r4$	$r4-r5$	p-val nor[†]	p-val non[‡]
L to L	NE	−28.64	−26.47	−2.45	0.34	0.00	0.00
	Data	−7.29	−9.63	−9.44	−8.45	0.54	0.31
L to H	NE	3.96	9.23	24.32	25.96	0.00	0.00
	Data	13.21	13.27	15.92	17.49	0.02	0.00
H to L	NE	−21.40	−19.00	−5.56	−2.10	0.00	0.00
	Data	−5.95	−5.79	−4.98	−2.41	0.11	0.06
H to H	NE	2.50	3.36	19.63	22.67	0.00	0.00
	Data	13.29	15.26	15.69	16.03	0.33	0.01

† ANOVA test.
‡ Kruskal–Wallis test.

the new box is above average, the increase in bids should be more dramatic in late rounds than in early rounds. Conversely, when the new box is below average, the decrease in bids should be higher in early rounds than in late rounds.

The actual average changes in bids do not exhibit these patterns. Subjects do change their bids when new information is disclosed (that is, there is no strong evidence of anchoring effects). However, the magnitudes of the average changes in bids across rounds are very different from NE predictions, and we do not observe the predicted marked difference between early and late rounds. Even though the difference across rounds is significant at the 5% level in two groups and at the 10% level in three groups according to the non-parametric test, the patterns are erratic and the magnitudes are small. As an illustration, in the ‘H to H’ group NE predicts the increase in bids to be almost 6 times higher in $r3-r4$ than in $r2-r3$, whereas in the data the increase is about 3%. Overall, at the aggregate level, subjects react to the amount of new information but not to its type. This finding is summarized in the following result.

Result 2. Hypothesis 2 is not supported by the data. The reaction of subjects to new information is largely independent of the type of information revealed (public vs. private).

5. Cluster analysis

The aggregate analysis establishes that bids per round depart from NE predictions, and that deviations are related to an incorrect treatment of information. However, Fig. 2 also reveals a large dispersion in deviations across rounds. It is therefore plausible that different groups of subjects behave differently in each round. To study this question, we search for trends at a disaggregate level. One possible approach is to do a subject-by-subject analysis (as in Costa-Gomes et al. (2001)). Even though this is in theory the most informative strategy, the reduced number of observations for each individual in each round would prevent us from making confident assessments. We therefore take an alternative approach, which is to search for clusters of subjects (as in Camerer and Ho (1999) and Brocas et al. (2014b)). This is an intermediate approach, as the aggregate approach implicitly assumes a single cluster is of interest while the subject-specific approach requires each subject to be in a singleton cluster. One advantage of the method is to provide an implicit measure of how well these two extreme cases capture the observed behavior.

5.1. Method

We do not know a priori the behavioral types of our subjects nor the shape of their actual bidding function. We cannot therefore assume confidently that their behavior is generated by some predetermined model. One agnostic way to reveal types is to search for patterns of deviations from NE across rounds and to group subjects according to those patterns. A follow-up analysis of each cluster can then reveal the causes of the associated patterns and help identify types.[8]

To find the clusters, we use for each of the 52 subjects the average deviation from NE in each round. Each subject is thus represented by five averages (rounds 1–5). There is a wide array of heuristic clustering methods that are commonly used but they usually require the number of clusters and the clustering criterion to be set ex-ante rather than endogenously optimized. By contrast, mixture models treat each cluster as a component probability distribution. Thus, the choice between different numbers of clusters and different models can be made using Bayesian statistical methods (Fraley and Raftery, 2002). Note that popular heuristic approaches such as ‘k means clustering’ are equivalent to mixture models where a particular covariance structure is imposed.

Since we do not want to presuppose a particular structure, we implement a model-based analysis with an endogenously optimized number of clusters. We consider a maximum of ten clusters and assume a diagonal covariance matrix. This implies zero correlation between the dimensions and no restriction on the variance. We first fix the number of clusters from 1 to

[8] This is by no means the only possible grouping strategy. Brocas et al. (2014b) for example collect attentional data and cluster subjects by their choice and lookup patterns. An alternative possibility would be to cluster subjects according to their deviation from the empirical best response. One advantage of our clustering method is that we can determine if the subjects who play close to Nash also react to different types of information as predicted by theory (see Section 5.3).

Table 5
Average gains by cluster.

Cluster	1	2	3	4	5	6
Mean	9.56	10.12	10.46	4.73	12.31	6.97
St. Dev.	(5.39)	(6.38)	(5.55)	(4.57)	(6.35)	(5.77)

10, and for each model we estimate the covariance matrix as well as the clustering that maximizes the likelihood function. We use random clustering as an initial guess.[9] Overall, for any possible number of clusters we obtain a clustering and a covariance matrix for each cluster, and we compute the corresponding Bayesian Information Criterion (BIC). Given this information, the optimal number of clusters is the one for which BIC is maximized. For our data, the BIC is maximized for 6 clusters with diagonal covariance matrix. These clusters, labeled 1 to 6, contain 11, 13, 6, 6, 9 and 7 subjects respectively. Notice that clusters are of different but comparable size, although this does not necessarily need to be the case.

5.2. *Bidding behavior by cluster*

In order to determine the properties of our clusters, we perform the same aggregate analysis as in Section 4 for each cluster separately. Table 5 reports the average gains in each cluster. Table 6 presents for each cluster the equivalent of Table 4, that is, the change in bids conditional on the type of information revealed. Finally, Fig. 3 is the equivalent of Fig. 2 for each cluster, that is, the average deviation from NE predictions per round.

Clusters 1 and 2 are closest to the theory. On average, they bid close to NE (Fig. 3). They also react differently to the different types of information. This reaction shares the qualitative properties of the theory. Yet, significant quantitative departures can be noted: subjects do not react nearly as much as theory predicts and they do not react uniformly over all four groups (Table 6). A few other differences relative to NE can be noted. Subjects in cluster 1 slightly overbid in every round while subjects in cluster 2 slightly underbid in every round. Interestingly, even though they bid close to Nash, these subjects do not obtain the highest payoffs. This is true because they do not best respond to the empirical distribution.

Cluster 3 is composed of a relatively heterogeneous group of subjects who underbid significantly. They change their bids across rounds but in an unpredictable way (often in the direction opposite from the theoretical prediction), suggesting that they do not realize the presence of different types of information. They obtain relatively high payoffs because their underbidding strategy "coincides" often with the best response to the empirical distribution.

Subjects in cluster 4 overbid significantly in every round and are very homogeneous. The average change in bids of this cluster is similar in all rounds, which means they treat private and public information in the same way. Their average gains are lowest given their substantial overbidding and the optimality of underbidding.

Cluster 5 is an interesting group of subjects. On the one hand, they bid on average close to Nash, and with no systematic deviation. In that dimension they look closest to rational players. On the other hand, they do not have a discernible pattern regarding the change in bids over rounds, which casts doubts about their understanding of the different types of information. They obtain the highest gains both overall and per round since their bidding strategy is closest to best response to the empirical distribution.[10]

Last, subjects in cluster 6 underbid substantially (most notably in round 1) and are extremely heterogeneous. They react tremendously to new information but very similarly if it is private or public. Their bids are significantly lower and more dispersed than those of cluster 3. Subjects in this cluster lose the auction most of the time and therefore obtain small payoffs. The findings are summarized below.

Result 3. Subjects in different clusters have different departures from NE, reaction to information, and degrees of heterogeneity which can be summarized as:

Cluster	**Difference from NE**	**Type of info. matters**	**Heterogeneity**
1	Small/Overbid	Yes	Small
2	Small/Underbid	Yes	Small
3	Large/Underbid	No	Large
4	Large/Overbid	No	Very small
5	Small/Round dependent	No	Small
6	Very large/Underbid	No	Large

Overall, as in previous studies (e.g., Crawford and Iriberri, 2007; Brocas et al., 2014b), we find clusters of subjects characterized by homogeneity within groups and heterogeneity across groups. The heterogeneity across clusters suggests that subjects may have different cognitive abilities. This is most apparent for clusters 1 and 2 on one end and 4 and 6 on the other. Subjects who strongly underbid (cluster 6) or systematically overbid (cluster 4) are likely to use simple heuristics. They fail

[9] We ran the model several times and the results were consistent. We use the EM algorithm for maximum likelihood estimation of multivariate mixture models.

[10] It would be interesting to investigate whether these subjects learn over time to best respond to the empirical behavior of the population. We could not perform this analysis due to the reduced number of observations.

Table 6
Average change in bids over rounds per cluster.

			$r1-r2$	$r2-r3$	$r3-r4$	$r4-r5$	p-val nor[†]	p-val non[‡]
Cluster 1	L to L	NE	−29.46	−24.07	−3.15	−2.13	0.00	0.00
		Data	−9.55	−9.02	−9.95	−15.15	0.35	0.31
	L to H	NE	2.40	7.15	23.63	26.36	0.00	0.00
		Data	8.56	8.70	11.83	12.74	0.11	0.09
	H to L	NE	−21.13	−19.55	−5.67	−1.03	0.00	0.00
		Data	−5.69	−8.38	−5.97	−3.24	0.27	0.31
	H to H	NE	2.01	4.30	20.18	22.82	0.00	0.00
		Data	10.88	12.36	15.48	16.48	0.08	0.03
Cluster 2	L to L	NE	−26.63	−27.04	−2.09	1.47	0.00	0.00
		Data	−5.88	−9.32	−7.75	−6.56	0.64	0.45
	L to H	NE	3.86	10.04	24.12	27.13	0.00	0.00
		Data	11.42	13.12	17.58	22.31	0.00	0.00
	H to L	NE	−21.39	−19.23	−5.18	−3.22	0.00	0.00
		Data	−8.45	−8.22	−3.76	−3.43	0.21	0.04
	H to H	NE	2.86	3.50	20.80	23.89	0.00	0.00
		Data	11.55	15.00	14.68	17.21	0.20	0.05
Cluster 3	L to L	NE	−28.47	−27.44	−3.37	−0.15	0.00	0.00
		Data	−2.60	−5.95	−9.48	−7.00	0.62	0.39
	L to H	NE	4.63	9.45	25.89	25.46	0.00	0.00
		Data	10.15	16.19	7.44	14.71	0.36	0.61
	H to L	NE	−20.65	−23.49	−6.78	−0.22	0.00	0.00
		Data	−6.96	−0.78	−9.29	3.00	0.03	0.08
	H to H	NE	3.26	3.23	18.14	24.39	0.00	0.00
		Data	15.46	17.08	12.96	18.17	0.74	0.55
Cluster 4	L to L	NE	−27.03	−25.18	−5.13	1.80	0.00	0.00
		Data	−14.52	−12.29	−17.82	−12.57	0.37	0.47
	L to H	NE	4.67	7.90	26.78	26.29	0.00	0.00
		Data	12.77	7.94	15.14	12.42	0.30	0.20
	H to L	NE	−22.33	−18.32	−4.98	−6.38	0.00	0.00
		Data	−7.68	−12.48	−5.95	−14.92	0.08	0.10
	H to H	NE	3.73	1.39	20.21	20.52	0.00	0.00
		Data	14.93	15.00	14.00	11.84	0.74	0.61
Cluster 5	L to L	NE	−31.22	−28.98	−0.13	−0.58	0.00	0.00
		Data	−8.89	−13.55	−12.85	−10.17	0.75	0.62
	L to H	NE	5.22	8.70	23.38	24.30	0.00	0.00
		Data	19.66	10.39	20.25	17.25	0.23	0.19
	H to L	NE	−19.66	−15.93	−5.40	−0.76	0.00	0.00
		Data	−4.81	−4.55	−9.61	−5.85	0.37	0.46
	H to H	NE	2.41	2.23	18.48	22.21	0.00	0.00
		Data	11.14	8.64	11.36	15.77	0.06	0.19
Cluster 6	L to L	NE	−29.28	−27.25	−1.16	1.34	0.00	0.00
		Data	−1.76	−5.48	−0.04	−3.66	0.89	0.81
	L to H	NE	3.51	11.54	22.76	24.89	0.00	0.00
		Data	17.41	21.88	23.19	30.40	0.29	0.57
	H to L	NE	−23.64	−19.43	−5.81	−2.69	0.00	0.00
		Data	0.33	3.83	2.18	8.32	0.60	0.12
	H to H	NE	1.55	4.23	19.16	21.84	0.00	0.00
		Data	20.90	28.11	30.22	16.29	0.28	0.47

[†] ANOVA test.
[‡] Kruskal–Wallis test.

to realize the link between bids and information and end up collecting the smallest payoffs. Subjects who play relatively close to NE (clusters 1 and 2) look sophisticated enough to approximate equilibrium behavior for all types of information but, at the same time, they overestimate the ability of their opponents to play Nash. As a consequence, they do not obtain the highest gains. The reasoning made by clusters 3 and 5, who obtain the highest payoffs, is more difficult to grasp. The strong underbidding and unpredictable changes of bids across rounds by cluster 3 suggests they may be using a 'lucky' heuristic that turns out to work well. As for cluster 5, their ability to bid close to NE and to depart from it at the correct time is intriguing. Perhaps they do realize the limitations of their opponents and take advantage of this knowledge.

Last, the comparison between Fig. 2 and 3 is interesting. Indeed, despite the substantial dispersion in the data at the aggregate level, there is relatively little dispersion within most clusters in each round. This suggests that there is little learning taking place in our auction. Each type of subject acts in a similar way in all trials of the same round. Moreover, each type of subject consistently adapts his behavior from round to round. Except for the clueless and volatile cluster 6 (13% of

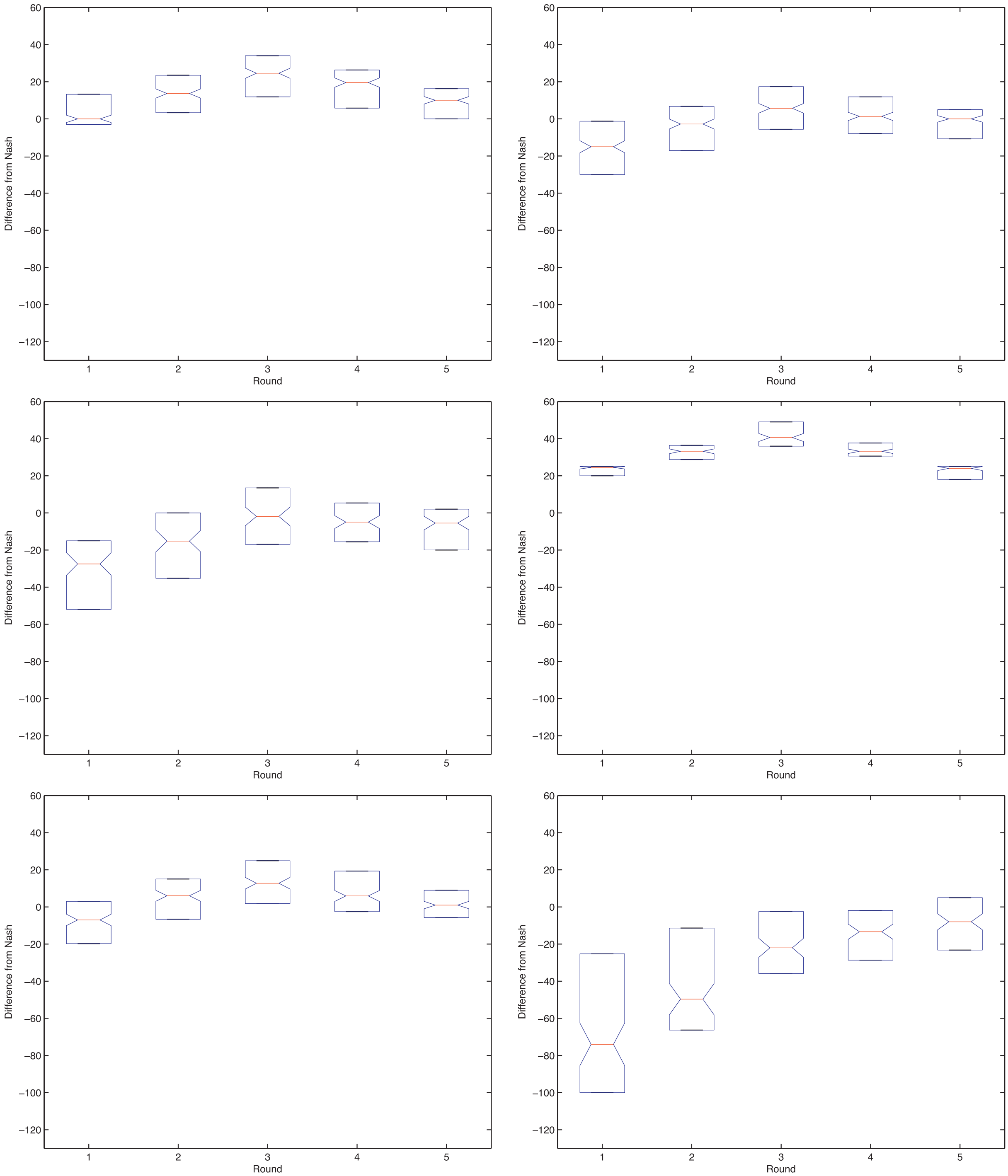

Fig. 3. Deviations from NE per cluster.

the population), subjects seem to be selecting a specific strategy in each round. Overall, there is a large heterogeneity in strategies between individuals but not much heterogeneity within individuals and across matches.

5.3. Analysis of bidding strategies for clusters 1 and 2

One important finding of the cluster analysis is that more than half of the participants (the 28 subjects in clusters 3, 4, 5 and 6) do not treat private and public information differently. The other half (the 24 subjects in clusters 1 and 2) do

Table 7
NE and FGLS regression per round for clusters 1 and 2.

	Round 1		Round 2		Round 3		Round 4		Round 5	
	NE	Data	NE	Data	NE	Data	NE	Data	NE	Data
Priv	1	0.48*** (0.008)	1.18	2.33*** (0.02)	1.42	1.99*** (0.01)	1.18	1.80*** (0.009)	1	1.17*** (0.007)
$(\text{Priv})^2$	N/A	−0.01	0.007 (0.00)	−0.03*** (0.00)	0.004	−0.01*** (0.00)	0.007	−0.015*** (0.00)	N/A	−0.006 (0.00)
$(\text{Priv})^3$	N/A	N/A	−0.0001	0.0001*** (0.00)	−0.0001	0.0000*** (0.00)	−0.0001	0.0000*** (0.00)	N/A	N/A
Pub	N/A	N/A	N/A	N/A	N/A	N/A	1	0.88*** (0.001)	1	0.91*** (0.000)
Constant	100	85.19* (0.19)	53.00†	53.00 (0.36)	−0.05†	25.60*** (0.34)	0.59†	17.56*** (0.20)	0	9.2*** (0.14)
F-test		5.8***								
Adjusted R^2		0.38								

Standard errors in parenthesis.
* Significantly different from NE at 90% confidence level (*t*-test).
** Significantly different from NE at 95% confidence level (*t*-test).
*** Significantly different from NE at 98% confidence level (*t*-test).
† These values are not 50, 0 and 0 respectively because we are using a polynomial approximation of NE.

realize to some extent that the type of information matters. In this section, we study in more detail the relationship between the empirical and NE bidding functions of these subjects. Given these subjects bid reasonably close to equilibrium, we will estimate a bidding function that keeps the main properties of the NE bidding function but allows for slight departures. This is explained more carefully below.

The NE bidding function is a linear function of public information (with slope 1) and a polynomial function of private information. In rounds 1 and 5, the polynomial is of degree 1, whereas in rounds 2, 3 and 4 it is the ratio of two higher order polynomials (see Table 1). We consider a polynomial approximation of our bidding function. Namely, for each round, we compute a cubic approximation in which we set the following relationship between the NE bid, b^r, and the various types of information:

$$b^r = \alpha_0^r + \alpha_1^r Priv^r + \alpha_2^r (Priv^r)^2 + \alpha_3^r (Priv^r)^3 + \alpha_4^r Pub^r + \eta_{Priv^r}$$

In this equation, superscript r denotes the round, *Priv* is the variable of private information and *Pub* is the variable of public information. The constant term α_0^r is the coefficient of common uncertainty, that is, the expected number of tokens in the boxes nobody observes. These are 100 in round 1, 50 in round 2 and 0 in the remaining rounds under the exact polynomial expression for *Priv*. The coefficient of public information, α_4^r, is relevant only in rounds 4 and 5 ($\alpha_4^1 = \alpha_4^2 = \alpha_4^3 = 0$). It is equal to 1 since both bidders compete à la Bertrand. Also, α_1^r, α_2^r and α_3^r are the coefficients for the cubic approximation of private information. Finally, η_{Priv^r} is the error term for each level of private information. It is different from zero in rounds 2, 3 and 4, where the cubic formulation of private information is only an approximation. The α^r-coefficients are reported in Table 7 for each round.[11]

If subjects play according to NE theory, they should produce bids consistent with b^r and parameters α_k^r. Given we know they do not exactly bid according to the model, we will allow them to bid according to a modified bidding function that preserves the overall NE structure but allows for different parameters. We will then fit this modified bidding function for the 24 subjects in clusters 1 and 2 to understand and compare the parameters we obtain with α_k^r. More precisely, we consider the following regression:

$$b_o = \beta_0 + \sum_{r=1}^{4} D_r [\beta_0^r + \beta_1^r Priv_o^r + \beta_2^r (Priv_o^r)^2 + \beta_3^r (Priv_o^r)^3 + \beta_4^r Pub_o^r] + \varepsilon_o$$

where superscript r denotes the round, subscript o denotes the observation and D_r is a round specific dummy. We see the similarity with the NE approximation: the α_k^r-coefficients have been replaced by β_k^r-coefficients with the same interpretation. We compute the coefficients of the Feasible Generalized Least Squares (FGLS) Random Effects regression for each of the variables and the t-test to check if the coefficients are significantly different from those predicted by NE (α_r^k parameters above).[12] We also perform a global significance F-test to inspect if, overall, the data bidding function is different from the NE bidding function. Fig. 4 and Table 7 display the results of this exercise.

[11] We opted for a cubic rather than quadratic approximation, because the latter performs badly for extreme values of private information. For example, in round 3, the quadratic approximation of NE has a constant term of -20 instead of the theoretical prediction of 0.

[12] The FGLS estimator makes use of the panel data structure to get more precise coefficients. We also performed the Hausman test and we could reject the presence of unobserved fixed effects. The variance estimator is clustered by subject.

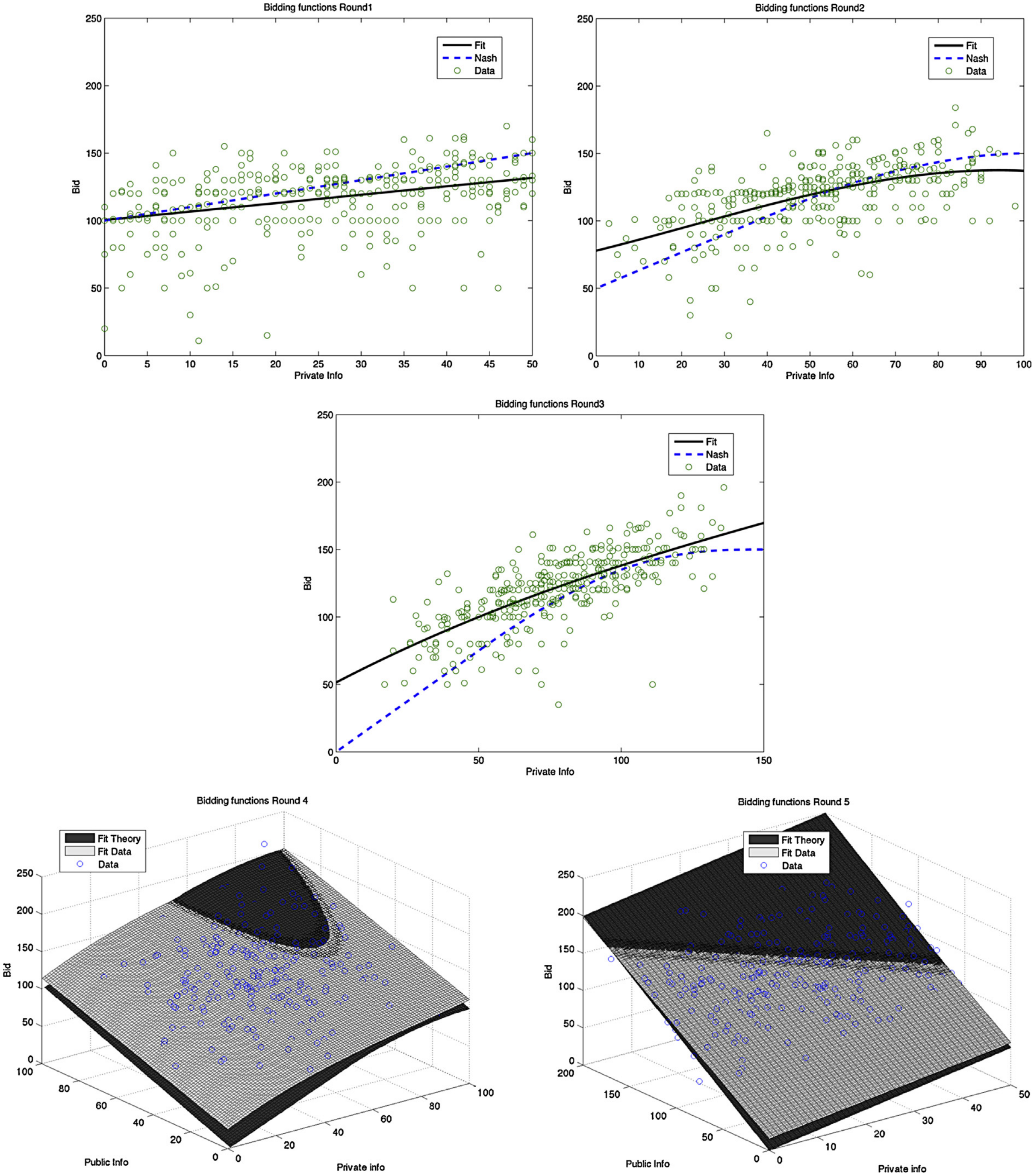

Fig. 4. NE and FGLS regression for clusters 1 and 2.

First, compared to NE, the proportion of the bid driven by common uncertainty is smaller in round 1, similar in round 2, and higher in the other rounds. Overall, deviations from NE regarding common uncertainty are hump-shaped, and largest in round 3. This result follows from a comparison between the estimated β_0^r-coefficients and the predicted NE α_0^r-coefficients. Second, subjects react less to public information than what theory predicts, although the differences are not large. Indeed, β_4 is close to but smaller than the corresponding NE prediction in the relevant rounds 4 and 5.[13] This results in overbidding

[13] Bids that are lower than NE predictions vis-à-vis public information is equivalent to prices that are higher than NE predictions in Bertrand competition games, a result found in Abbink and Brandts (2008).

for low values of public information and underbidding for high values of public information. Notice that risk aversion would impact both private information and common uncertainty, but not public information.[14] Third, a close inspection of Fig. 4 suggests that subjects react less to private information than what NE predicts in round 1, and therefore underbid for all values of private information in that round. In rounds 2 and 4, subjects overbid for low values and underbid for high values of private information whereas in round 3 there is consistent overbidding. We summarize the findings in the following result.

Result 4. The subjects who play close to NE exhibit nonetheless some departures with respect to all three types of information: (i) they under-react to common uncertainty in early rounds and over-react in late rounds; (ii) they consistently under-react to public information; and (iii) they typically overbid when their private information is large.

6. Conclusions

This paper incorporates two novel features that facilitate the study of bidding behavior in common value auctions. First, it divides the good into three elements: those known by both bidders, those known by one bidder, and those known by no bidder. Second, it varies the relative importance of each element holding everything else constant. The paper replicates the overbidding tendency documented in previous research (Kagel and Levin, 1986, 2008)). More importantly, we show that less than half of the subjects grasp the idea that different types of information imply different adjustments of bids. The rest treat new information in the same way, independently of the type of information being revealed. Those who understand that the information structure matters still under- or over-react to information. The results are consistent with our companion paper (Brocas et al., 2014a) where we also find large deviations from Nash and imperfect account of different types of information in a second price sealed bid auction.

We believe this is an important point with relevance in many experimental designs. For instance, the auction studied in this paper has a signal extraction problem which is similar to other games with common values and private information: informational cascades, information aggregation through voting, and jury verdicts, just to name a few. Our result suggests that for these settings, one should pay close attention to the way in which information is presented. Different models may have qualitatively the same theoretical predictions. In practice, however, the behavior of subjects may be affected by the presence and relative importance of peripheral elements such as public information and common uncertainty.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jebo.2014.10.015.

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[14] Holt and Sherman (2014) show in a specific setting that risk aversion does not affect the bidding function. However, for general distributions two effects operate in opposite directions for risk averse bidders: an uncertain prize is valued less (implying lower bids) but in order to reduce the uncertainty associated to losing the auction, the bidder prefers to bid more.