The Winner's Curse: Conditional Reasoning and Belief Formation*

Christian Koch[†] and Stefan P. Penczynski[‡]

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Abstract

In explaining the winner's curse, recent approaches have focused on one of two cognitive processes: conditional reasoning and belief formation. We provide the first joint experimental analysis of the two obstacles. First, we observe significant differences in behavior between a simple common-value auction and a transformed version of this auction that differs in not requiring conditional reasoning. Second, assistance in belief formation leads to significant behavioral changes in both games. The two effects are of similar magnitude and amplify each other when present jointly. We conclude that the combination and the interaction of the two cognitive processes in auctions lead to relatively low strategic sophistication compared to other domains. The study's focus on games' objective cognitive challenges is potentially useful for predictions across games and complements the common focus on behavioral models and their explanatory power.

JEL classification: D44, D82, C91

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[†]New York University Abu Dhabi (NYUAD), A5 - 1131, PO Box 129188, Abu Dhabi, UAE. Email: christian.koch@nyu.edu.

[‡]University of Mannheim, L7, 3-5, 68131 Mannheim, Germany. Email: stefan.penczynski@uni-mannheim.de.

1 Introduction

The "winner's curse" (WC) in common-value auctions (CVA) refers to systematic overbidding relative to Bayesian Nash equilibrium (BNE) that leads to massive losses for winners in field settings and laboratory experiments.[1] This phenomenon is one of the most important and robust findings in empirical auction analysis and has generated ample theoretical work.

Two main departures from BNE have been modeled. Both maintain the assumption that players best respond to their beliefs but relax the requirement of consistency of beliefs. First, in equilibrium models such as cursed equilibrium (CE, Eyster and Rabin, 2005), behavioral equilibrium (Esponda, 2008), and the application of analogy-based expectation equilibrium to auctions (Jehiel, 2005; Jehiel and Koessler, 2008), beliefs do not fully take into account information revealed about underlying signals, capturing a non-optimal adjustment for the information revealed by winning. Second, the level-k model assumes non-equilibrium beliefs resulting from iterated best responses (Nagel, 1995; Stahl and Wilson, 1995). It has been applied to private information games such as auctions and zero-sum betting (Crawford and Iriberri, 2007; Brocas, Carrillo, Wang, and Camerer, 2014). This approach can implicitly capture non-optimal adjustment when assuming beliefs of uninformed play.

Doubts have been cast on the sufficiency of these *belief-based* models to explain auction behavior. With an innovative semi-computerized version of the maximal game, Ivanov, Levin, and Niederle (2010, ILN) experimentally study whether these models can explain the WC and claim that they cannot. Along these lines, Charness and Levin (2009, CL) use computerized sellers in an acquiring-a-company game and document that subjects have a more general problem with *conditional reasoning* – drawing appropriate conclusions from hypothetical events – that seems not to be fully captured by the relaxation of beliefs.

In turn, however, Costa-Gomes and Shimoji (2015) criticize ILN's use of game theoretical concepts when the interaction with a known computer program is a single-person decision problem. They argue that belief-based models are indeed compatible with some observations from ILN's experiment. Moreover, Camerer, Nunnari, and Palfrey (2015) suggest on the basis of Quantal Response Equilibrium

[1] See Capen, Clapp, and Campbell (1971) and Roll (1986) for evidence from the oil industry and corporate takeovers, respectively, and Bazerman and Samuelson (1983), Kagel and Levin (1986), Avery and Kagel (1997), Goeree and Offerman (2002), Lind and Plott (1991), Grosskopf, Bereby-Meyer, and Bazerman (2007), and the literature discussed in Kagel and Levin (2002) for experimental evidence.

(QRE, McKelvey and Palfrey, 1995) that imprecise best responses combined with non-equilibrium beliefs could explain observed behavior.

This discussion shows that no consensus has been reached on how to model the WC. In this study, we do not test concrete models of reasoning, but take a step back and focus on two objective game complexities whose relative importance in causing the WC is – as shown above – disputed in the literature: *conditional reasoning* vs. *belief formation*. Both activities are indispensable to reach a best response. In any strategic situation, subjects have to *form beliefs* about their opponents' behavior in order to know what to best respond to. In CVAs, best responding further requires *conditioning* on apprehended hypothetical situations induced by the game's structure. For example, the bid is only relevant when winning, which implies the valuable information that all others have bid less. Crucially, which of the two complexities poses a more substantial challenge for bidders in CVAs remains an open empirical question. By providing the first joint experimental analysis that disentangles the impact of these two cognitive processes in a CVA setting, we are able to determine – as our paper's main contribution – whether the WC is predominantly driven by *conditional reasoning* or *belief formation*. Our approach to study strategic behavior with a focus on objective game complexities establishes how two of those complexities – which can be found in a variety of important games – generally affect behavior. Notably, this analysis is not constrained by a more specific structure on how people think about these problems. Like physics can predict the bending of a horizontal steel bar due to vertical forces without a detailed model of the tensions inside the bar, we propose to relate the impediment of immediate equilibrium play to objective game complexities such as the need for conditional reasoning or for elements of belief formation. This view entails particular potential for improving predictions across very different games, an area of study so far put in second place.

More precisely, our starting point is a simple first-price CVA adapted from Kagel and Levin (1986). At the core of our investigation, we propose a transformation of this game that maintains the strategic nature of the original auction game in terms of best response functions and equilibria but removes the need to engage in conditional reasoning. Even in a human-subject setting, and hence under regular belief formation, this allows us to cleanly identify the effect that this cognitive activity has on bidding behavior and the WC. Independently of this variation, we further change the need to form beliefs in two ways. First, we fully remove the need to form beliefs by letting subjects play against naïve computer opponents that follow a known simple strategy. Second, we remove crucial parts of belief formation but maintain the strategic uncertainty associated with human opponents when we let subjects play against human opponents subsequently to play against computer. The preceding encounter with the naïve computer provides subjects with a first basic belief or scenario about opponents' behavior which they otherwise have to craft themselves.

Following our focus on objective cognitive complexities, we intend to measure their behavioral impact in a flexible and general way. In a simple and intuitive formalization of this approach, we normalize the distance in the action space with a measure μ, between optimal or equilibrium play, $\mu^e = 0$, and uninformed random play, $\mu^u = 1$, and judge a cognitive complexity by the sign and magnitude of the change $\Delta\mu$ caused in the direction away from optimal behavior.

In a modified auction setting that requires neither conditional reasoning nor belief formation for optimal behavior, we observe bids that are close to equilibrium play with μ of 0.29. From there, we obtain three main results. First, introducing the need to condition – without requiring any belief formation – makes bids significantly higher and further away from optimal play with $\Delta\mu = 0.18$, and increases the incidence of the WC by 15 percentage points. Second, requiring partial or full belief formation – in the absence of conditional reasoning – leads to remarkably similar increases in bids, $\Delta\mu$ of 0.15 and 0.20, and raises the number of subjects facing losses by 8 to 11 percentage points, respectively. Interestingly, the partial belief manipulation shows that the mere need to form a first belief, while leaving strategic uncertainty unchanged, already proves challenging for subjects. Third, no generally significant differences emerge when comparing the magnitude of the effect of conditional reasoning and belief formation. Although both effects individually worsen game play, the fraction of plausible bids still remains non-negligible. Combining conditional reasoning and full belief formation results in behavior fairly far away from equilibrium, $\mu = 0.81$, as usually observed in CVA settings. Interestingly, the combination of both effects, $\Delta\mu = 0.52$, leads further away from equilibrium than expected by the sum of the two individual effects, $\Delta\mu = 0.38$, implying that the two strengthen each other and exhibit what we call *cognitive diseconomies*.

Our results suggest that both conditional reasoning and belief formation are important drivers of the WC. The introduction of either complexity individually has a significant, but limited impact. Crucially, however, the two effects interact and in combination lead to widespread implausible play of weakly dominated strategies. Some subjects seem to not even craft any basic belief. Indeed, conditioning on winning is only informative with a concrete belief and the necessity to condition presents a structural complexity that could make belief formation more difficult, potentially in turn affecting the conditioning. Our results show that this intertwining is empirically relevant: the two cognitive complexities jointly produce an extreme case of game-dependent sophistication that is not fully captured by belief-based models. This finding reconciles CL's and ILN's critique of those models in common-value auction settings with the strong support for them from other domains in which conditional reasoning is not required (see Crawford, Costa-Gomes, and Iriberri, 2013).

A number of further papers are closely related to our work. Levin et al. (2016) analyze the conditioning problem in the WC in more detail by separating the involved Bayesian updating from non-probabilistic reasoning. In particular, the authors compare results from a first-price auction with a strategically equivalent Dutch-CVA that makes the conditioning problem more salient. Relatedly, but in non-auction settings, Esponda and Vespa (2014), Louis (2015), and Ngangoue and Weizsäcker (2015) have analyzed conditioning in more depth by separating two involved steps – hypothetical thinking per se and conditioning on hypothetical events – by comparing behavior in simultaneous and sequential games. With our transformation, we propose a complementary way of studying conditional reasoning in auction settings. Crucially, we do not provide such a differentiated analysis of conditional reasoning itself but relate the impact of the overall conditioning effect in causing the WC to the impact of belief formation. Moreover, Charness, Levin, and Schmeidler (2014) observe the WC in a generalized information environment in which bidders hold identical and public information. Their innovative design allows them to disentangle on the one side the influence of heterogeneity in estimation of the common value and on the other side the influence of non-optimal bidding behavior. They show that both are relevant for the WC. Complementing their results, our study only focusses on the bidding behavior but additionally disentangles the role of conditional reasoning and belief formation. Finally, Levin and Reiss (2012) construct a behavioral auction design in which the payment rule incorporates the adverse selection problem that is at the origin of the WC. They observe that the WC is still present in their data. The authors adjust the payment rule but do not transform the auction game as we do.

Due to our method of transformation, our paper also relates to the broad set of studies that investigate behavior using strategically very similar games. The largest fraction of those studies considers framing effects that influence subjects' behavior but do not result from the strategic nature of the situation (for example Tversky and Kahneman, 1986; Osborne and Rubinstein, 1994; Chou et al., 2009). Another methodologically interesting instance of strategic equivalence is the experimental, so-called "strategy method" in which participants make contingent decisions for all decision nodes that they will possibly encounter in a game (Brandts and Charness, 2011). In a different manner, strategically equivalent versions of a game can facilitate the investigation of particular aspects of behavior. For example, Nagel and Tang (1998) use a repeated, normal-form centipede game to investigate learning behavior without aspects of sequential reciprocity.

In our study, we craft two similar games that differ in the cognitive process under investigation: conditional reasoning. To the best of our knowledge, our experiment is the first that uses such a transformation as a means to investigate the impact of this particular cognitive activity in strategic reasoning. By this virtue, our approach opens further avenues for investigation in settings with similar cognitive processes. For example, conditioning on being pivotal in a jury decision is part of strategic voting (Feddersen and Pesendorfer, 1998) and conditioning on message selection is part of being optimally persuaded (Glazer and Rubinstein, 2004).

2 Design and Hypotheses

In our experimental design, we will use two different games: a simplified standard *auction game* that serves as the basis for constructing a *transformed game* that does *not* require conditional reasoning. The starting point for both games is a standard first-price CVA setting as in Kagel and Levin (1986). Here, each of the n bidders receives a private signal $x_i \in [W^* - \delta, W^* + \delta]$, with $\delta > 0$, which is informative about the common value of the auctioned item $W^* \in [\underline{W}, \overline{W}]$. Bidders make bids a_i in a sealed-bid first-price auction in which the highest bidder wins the auction and pays his bid. The payoff of the highest-bidding player who wins the auction is $u_i = W^* - a_i$. In case a bidder does not make the highest bid, his payoff is $u_i = 0$.

2.1 The Games

2.1.1 Auction Game

We simplify this general setting – to be able to later construct the transformed game – mainly by allowing only for two signals and two players $n = 2$. Bidders receive a private binary signal $x_i \in \{W^* - 3, W^* + 3\}$ drawn *without replacement*. Hence, bidders know that the other bidder receives the opposite signal but do not know which one it is. Let us denote the state of i's world by $\omega_i = \{h, l\}$, indicating whether W^* is high or low relative to i's signal, so that $x_i|h = W^* - 3$ and $x_i|l = W^* + 3$.[2] The common value W^* is uniformly distributed in the interval $[25, 225]$. To ensure an equilibrium in pure strategies, we only allow bids $a_i \in [x_i - 8, x_i + 8]$. As a tie-breaker in case of identical bids, the lower-signal player wins the auction. As in Kagel and Levin (1986), bids are made in a first-price sealed bid auction.

Consider the following example as illustrated in figure 1. The male player i receives the signal $x_i = 125$. Hence, i's bids are limited to $a_i \in [117, 133]$. Moreover, i knows that with 0.5 probability the value of the item is either 3 units above or 3 units below his signal, $W^*|h = 128$ or $W^*|l = 122$. When subjects make their decisions in the experiment, the computer presents these two values to the subjects as shown in figure 2. Moreover, to form a rational strategy, player i can *infer* that his female opponent j either has received a signal that is six points lower, $x_j|l = 119$, or six points higher, $x_j|h = 131$, depending again on the state of his own signal ω_i. When finding the best response to his beliefs, i has to condition on these two hypothetical events.

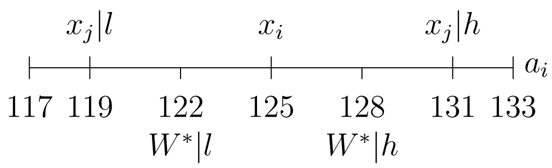


Figure 1: The example in the auction game.

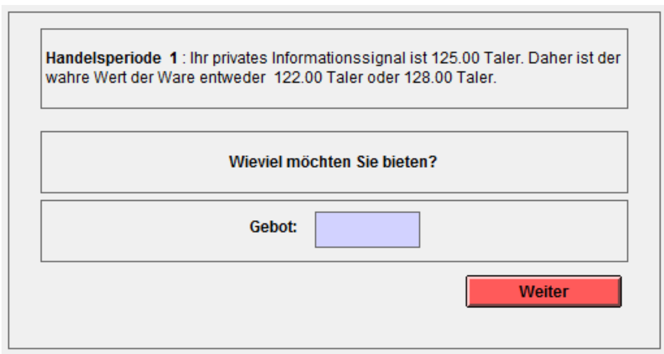


Figure 2: Screenshot auction game: "**Trading period 1**: Your private information signal is 125.00 Taler. Hence, the true commodity's value is either 122.00 or 128.00 Taler. **How much do you want to bid?**"

[2]In the remainder, for ease of exposition, any state indication will refer to ω_i and not ω_j.

This example also illustrates what we consider as *conditional reasoning*: First, subjects have to be able to think in hypothetical situations that are induced by the game's structure. In our design, they have to realize that due to the signal structure two different hypothetical situations are possible: receiving the higher or the lower signal, where the opponent has received the opposite signal. Afterwards, subjects have to condition on these two hypothetical events jointly when drawing appropriate conclusions about how to behave. Crucially, we do not conceptualize conditional reasoning in a formal model since our focus is not on the cognitive process of the subject but on the objective challenges posed by the game.

2.1.2 Underlying Structure of the Auction Game

To analyze the underlying structure of the auction game, we express subjects' strategies by *relative* bids with respect to their signal: $b_i = a_i - x_i$. Due to their relevance, we will call these relative bids just "bids" in the remainder and always specify when we talk about *absolute* bids a_i. This is only for analytical purposes, the instructions exclusively use absolute bids for both games and subjects make all their decisions in the same absolute metric.

Relative to the other player's bid b_j, i's strategies, b_i, lead to three kinds of interactions, as illustrated in figure 3(i). First, if player i overbids player j by at least 6 units – bridging the distance between signals in h – he always wins the auction, in both l and h. Second, conversely, if i underbids j by at least 6 units, he never wins the auction. Third, if i bids less than 6 units away from j's bid, he only wins the auction in l, not in h, reflecting the standard adverse selection problem common to CVAs. Within this range, bidding $b_i = b_j - 6 + \epsilon$, with a small $\epsilon > 0$, is optimal because it assures winning in l at the lowest price. Figures 3(ii)-(iv) show how the three kinds of interactions derive from the position of signals.

In particular, if player i *believes* that his opponent j just bids his signal, $b_j = 0$, player i has to *infer* that player j's absolute bid is either 119 or 131. Based on this inference, in case player i makes at least an absolute bid of 131, or $b_i = 6$, he will always win the auction. Bidding weakly below 119, or $b_i = -6$, results in never winning the auction. Finally, bidding above 119 but below 131 – resulting in an optimal bid of $119 + \epsilon$ for this set of strategies – leads to winning only when receiving the higher signal and, hence, with 50% chance. Thus, within the "win in l" set the winner always receives the higher signal and the smaller item value realizes.

Assuming risk neutrality, in the equilibrium of this game both players bid -8.

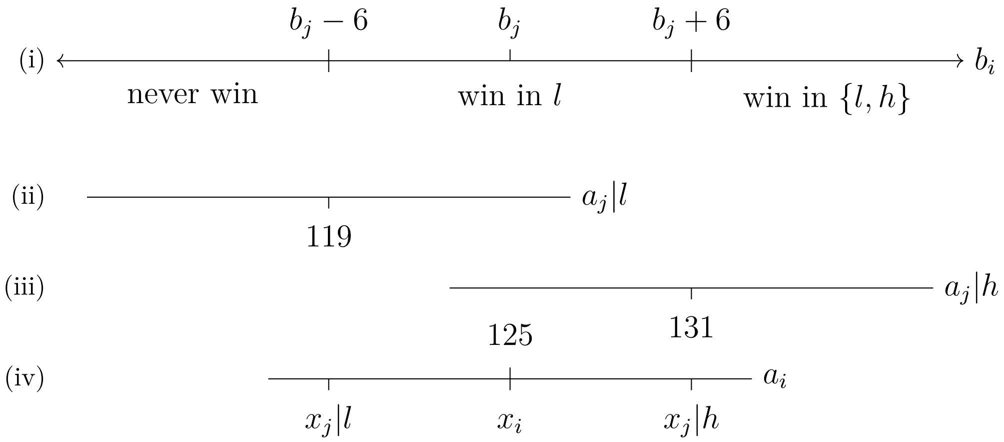


Figure 3: Three sets of relative bids b_i (i) induced by the relative position of signals x_i, $x_j|l$, and $x_j|h$, illustrated for the case of $b_j = 0$ (ii-iv).

Intuitively, when both players bid -8, each player wins the auction with 50% chance ("win in l"). From the perspective of the winner, the low value of the item realizes, $W^* = x - 3$. Deviating from this strategy, however, by always winning the auction ("win in $\{l, h\}$") with a higher bid of $b = -2$ leads to losses in state l that are not sufficiently compensated in state h. Similarly, "never win" cannot result in positive profits. By restricting the action set to $b \in [-8, 8]$, we ensure this pure equilibrium strategy (for details see proposition 1 below).[3]

2.1.3 Transformed Game

We construct the transformed game as a common-value auction without private signals but with special auction rules. These special rules reflect the underlying structure of the auction game, expressed in relative bids. By doing this, we maintain the strategic nature of the original auction game in terms of best-response functions and equilibria but remove the need to engage in conditional reasoning.

The transformed game has the following structure: We again have two players. These players do not receive any signals but are informed about the two possible values an item can take, W_l^* or $W_h^* = W_l^* + 6$. Here, our game is constructed such that W_l^* and W_h^* correspond to the possible values of the item from the point of view of a signal $\frac{W_l^* + W_h^*}{2}$ in the auction game. Hence, relative bids are defined as $b_i = a_i - \frac{W_l^* + W_h^*}{2}$ and thus differ only by a constant from absolute bids. These facts are, of course, unknown to subjects when they play the transformed game. As in the auction game, subjects are allowed to absolutely underbid W_l^* by 5 units

[3]Due to this structure, deviations to "never win" and "win in $\{l, h\}$" are not always possible.

and absolutely overbid W_h^* by 5 units, $a_i \in [W_l^* - 5, W_h^* + 5]$. In analogy to the auction game, the ranges of the values are $W_l^* \in [25, 219]$ and $W_h^* \in [31, 225]$.[4]

Subjects are told that the realization of the two possible values depends on chance and on both players' absolute bids. More precisely, instead of a simple first-price auction rule, subjects are provided with three special auction rules. First, if one player absolutely overbids the other player by at least 6 units, this player wins the auction for sure and either value realizes with probability of 0.5 ("win in $\{l, h\}$"). Conversely, if one player absolutely underbids the other player by at least 6 units, this player does not win the auction and his or her payoff is 0 for sure ("never win"). Lastly, if the difference between both players' absolute bids is smaller than 6 units, then the probability of each individual player to win the auction is 0.5, and the smaller value W_l^* realizes irrespective of which player wins the auction ("win in l"). The loser obtains a payoff of 0. Crucially, these rules reflect in absolute bids exactly the underlying sets of strategies of the auction game as expressed in relative bids. They spell out consequences explicitly so that subjects do not have to engage in conditional reasoning.

This can be illustrated by an example of the transformed game analogous to the auction-game example, as presented by Figure 4. Player i as well as his opponent j are informed that the auctioned item either has value $W_l^* = 122$ or $W_h^* = 128$. In the experiment, the decision screen presents these two values as shown in figure 5. Players' absolute bids are limited to $a_i \in [117, 133]$. Suppose that – analogous to the auction-game example – player i believes that his opponents j just bids the mean value of the item, $a_j = 125$ or $b_j = 0$. Just by consulting the auction rules, i knows that bidding at least 131, or $b_i = 6$, will result in always winning the auction, bidding weakly below 119, or $b_i = -6$, will result in never winning the auction, and bidding in between will result in winning the item with the lower value with 50%. Hence, where signals in the auction game induce a structure of two hypothetical events on which subjects have to condition their inferences, the rules of the transformed game already reflect these two hypothetical events and present the conditional inferences from these events in form of winning probabilities and the realized item value. Crucially, the last rule also incorporates – by the realization of the lower item value – that within the "win in l" set in the auction game, the winning player has the higher signal. Hence, to get to the equilibrium, i only has to find the best response to his beliefs by consulting the rules of the

[4] We choose the intervals such that the lowest and highest realizations are the same across the two games. Other ways of drawing this analogy are conceivable, however, this way is the most straightforward one.

game. No conditional reasoning on hypothetical situations induced by states of the world is necessary.[5]

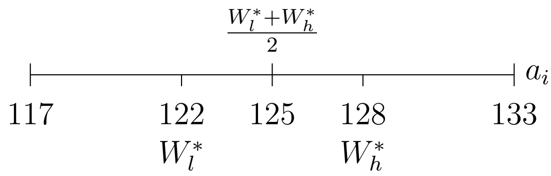


Figure 4: The example in the transformed game.

Since the special auction rules of the transformed game reflect the underlying structure of the auction game, best response functions in the two games describe the same optimal behavior when abstracting from boundary signals and assuming that players – as is true in equilibrium – bid type-independently in the auction game. Hence, by construction, equilibrium bids in the transformed game coincide with values of the equilibrium bid function in the auction game. Further, players in the two games face identical uncertainty, so that more general risk preferences than risk neutrality do not change the equivalence of the equilibrium strategies. Additional important consequences are that noise as modeled for example in Quantal Response Equilibrium cannot account for differences between the two games, neither can the fact that the equilibrium strategy is at the lower end of the action space, $b = -8$ (see also CL).[6]

Proposition 1. *The unique Nash equilibrium in the transformed game for both players is to bid $b^e = -8$.*

The Nash equilibrium relative bid function for both players in the auction game is denoted $b^e = b^*$. For signals $x \in [46, 228]$, any b^* takes the value

$$b^*(x) = -8. \tag{1}$$

Proof. See appendix A.3. ■

The intuition presented for the auction game in subsection 2.1.2 is also valid in the transformed game. Note, however, that there is a crucial distinction between

[5]Forming beliefs about others' behavior remains *unchangedly* necessary and can be conceived as thinking about hypothetical situations. Crucially, however, from these situations no further information about a state of the world can be inferred, an essential part of conditional reasoning.

[6]CL implement a corner equilibrium as well as an internal equilibrium and find no qualitative difference between them. In our auction game, no such simple modification is available because allowing for lower bids gives rise to a mixed strategy equilibrium. Importantly, we are mainly interested in treatment differences between similarly structured games, not absolute bid levels in individual games.

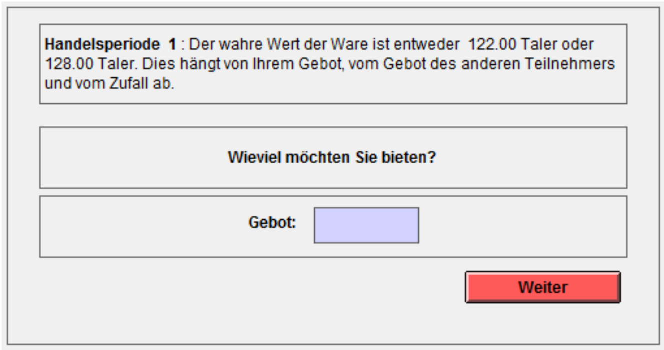


Figure 5: Screenshot transformed game: "**Trading period 1**: The true commodity's value is either 122.00 Taler or 128.00 Taler. The value depends on your bid, the other participant's bid and chance. **How much do you want to bid?**"

the two games. In the auction game, in equilibrium and whenever bids are in the "win in l" area, the conditional value of the item, $E[W^*|x_i, l] = x_i - 3$, is lower than the unconditional one, $E[W^*|x_i] = x_i$. This difference highlights the adverse selection problem present in this game. If bidders ignore this and bid $b > -3$, they lose money on average.[7] Crucially, the distinction between conditional and unconditional item value becomes obsolete in the transformed game since the conditional value of the item is already incorporated in the rules. Note, additionally, that the transformation generates common knowledge of the possible values of the item while the auction game's signal structure prevents this.

There, signals close to the end-point value of 25 reveal the value of the item fully to one player, providing incentives not to bid according to equation 1. For signal values up to 46, subjects' optimal bid function can be influenced through higher-order beliefs by those incentives as detailed in appendix A.3. We disregard the few observations that fall in this small range when analyzing our data and further discuss the matter in 3.4. Outside of this range, the differences in the information structure between the two games do not influence equilibrium behavior. Notably, the revelation of the item value through signals close to 225 creates further

[7] Some researchers define the WC as deviations from equilibrium bidding with less than normal profits (Crawford and Iriberri, 2007, CL). Kagel and Levin (1986) associate the WC with bids in excess of the conditional value since this entails negative profits *on average*, a more stringent definition. Empirically, we can analyze the differences between treatments in many ways, we report them both in terms of actual losses as well as differences from equilibrium. Kagel and Levin (1986) use the difference in strategic discounting between common-value and private-value settings as an indicator of the adverse selection problem. They show that for two players there is no difference in strategic discounting. This remains true in our setting as -8 remains the equilibrium strategy when signals determine the private value of bidders. For our purposes, however, this equilibrium comparison obstructs the view on important out-of-equilibrium effects of adverse selection, as still reflected by the difference of the conditional and the unconditional item value.

incentives for bidding low and thus does not change the equilibrium strategy.

2.2 Experimental Design and Procedures

The games implemented in the experiment differ along 2 dimensions. The first dimension relates to conditional reasoning, which subjects have to deal with in the auction game but not in the transformed game.

The second dimension is spanned by 2 different manipulations of belief formation that influence the extent to which subjects have to form beliefs about their opponent in order to know what to best respond to. In the full belief manipulation, subjects are confronted with naïve computer opponents, whose strategies are known. In sharp contrast to facing fellow human opponents, the need to form beliefs and to cope with strategic uncertainty is fully removed. The subjects are informed that the computer follows the naïve strategy $b^C = 0$, implying that it bids in absolute terms according to the signal or the mean value of the item, respectively. In the experiment, subjects have to round their bids to one cent of a unit. The best response is thus $BR(b^C) = -5.99$ (win in l). We deliberately do not implement a more complex or realistic strategy for the computer opponents due to their role in the next manipulation. Furthermore, subjects do not necessarily have to be able to best respond to complex belief distributions in the human opponent games either. When subjects realize in a first step that underbidding by $BR(b^C) = -5.99$ is the best response to naïve play, they might recognize the equilibrium strategy – which in turn is the best response to -5.99 – in a second step. In the partial belief manipulation, subjects face human opponents subsequent to interacting with the computer without receiving any payoff feedback in-between. The preceding encounter with a deterministically acting, naïve opponent already places subjects in a simple scenario providing a first basic belief how opponents may act. Subsequently, subjects can extend this simple scenario to craft a belief about human opponents featuring strategic uncertainty. Interestingly, this setting provides a valid alternative belief formation manipulation to the very particular single-person decision problem of facing computer opponents (see ILN, Costa-Gomes and Shimoji, 2015).

We use a within- and between-subject design, in which all subjects play all four different games but in different sequences. Table 1 illustrates our four treatments. The treatment name is derived from the first game in each treatment. Each treatment is divided in parts I and II. The $\mathcal{A}$ treatments start with the auction game (A) in part I and have the transformed game (T) in part II. In the $\mathcal{T}$ treatments, this sequence is reversed. Within each part of these $\mathcal{H}$ treatments,

	Sequence of games						
	Part I		Part II				
Treatment	1	2	3	4	*Game identifiers:*		
$\mathcal{AH}$	$\boldsymbol{AH}$	$AC_{\mathcal{AH}}$	$TH_{\mathcal{AH}}$	$TC_{\mathcal{AH}}$		A	auction game
$\mathcal{TH}$	$\boldsymbol{TH}$	$TC_{\mathcal{TH}}$	$AH_{\mathcal{TH}}$	$AC_{\mathcal{TH}}$		T	transformed game
$\mathcal{AC}$	$\boldsymbol{AC}$	$\boldsymbol{AH_{\mathcal{AC}}}$	$TC_{\mathcal{AC}}$	$TH_{\mathcal{AC}}$		H	human opponent
$\mathcal{TC}$	$\boldsymbol{TC}$	$\boldsymbol{TH_{\mathcal{TC}}}$	$AC_{\mathcal{TC}}$	$AH_{\mathcal{TC}}$		C	computer opponent

Notes: In order to distinguish games by the treatment they belong to, we add a treatment subscript, e.g. $AH_{\mathcal{AC}}$, whenever it is not the first game in the treatment. Our analysis focusses mainly on the six games in boldface.

Table 1: Sequence of games in the four treatments.

the opponents switch from human (H) to computer opponents (C). Subjects are instructed before each particular game. Hence, they know about the computer opponent and its strategy only after they have finished the initial game. In the $\mathcal{C}$ treatments, this switch is reversed from C to H. Hence, subjects face human after computer opponents ($\star H_{\star\mathcal{C}}$).[8]

Our design generates data for clear between-subject comparisons and also allows for rich within-subject analyses. The six games in boldface allow us to disentangle the effects of conditional reasoning and belief formation on game play using a between-subject analysis. The remaining games in part I allow us to analyze within-subject bid transitions from human to computer opponents. Part II provides further within-subject data on the learning transfer between auction and transformed games and vice versa as analyzed in appendix B.1. Data from all 16 games will be used to quantify the effect of cognitive complexities in a regression analysis.

In all treatments, the general instructions and the instructions for the games are read out aloud. We do not provide a control questionnaire because meaningful questions might highlight the adverse selection problem underlying the games. Instead, *frequently asked questions* that summarize main points of the games are read aloud. These FAQs have been generated based on trial sessions. Subjects play each specific game for three consecutive periods against randomly rematched subjects or the computer. Subjects are informed that they will first make all 12 decisions in the experiment before receiving any feedback.[9] We deliberately

[8]An expression with $\star$ refers to both A and T games, e.g. $\star H$ stands for the two games AH and TH. H alone refers generally to human opponents (including e.g. $AH_{\mathcal{AC}}$).

[9]Because subjects do not receive any feedback after playing one period, in principle, it would have been possible to just implement one period per game. However, implementing three periods allows us to see whether subjects consistently play the same strategy across three periods for different values of the signal.

rule out that subjects get any payoff information after each game to illuminate the mechanism behind the WC, undisturbed from learning through feedback. It has been shown that experiences with losses and simple learning strategies enable subjects to slowly avoid the WC. Crucially, they seem to do this without overcoming the underlying cognitive complexities insofar as they do not transfer knowledge to similar situations in the future (see Kagel and Levin, 2002, p. 337). Although it is interesting in itself to analyze how subjects adapt in the long run even without a deep understanding, our core interest is in (a) whether people's failure to *overcome* certain cognitive complexities causes the WC in the first place and in (b) which complexity is to blame. Focussing on initial responses allows tackling these questions and moreover enables a meaningful within-subject analysis. Instructions and FAQs are reprinted in appendices B.3 and B.4.

The experiments were conducted at the University of Mannheim in spring and autumn 2014. Overall, 12 sessions with 10 to 22 subjects in each session were run. In total, 182 subjects participated.[10] Participants received a show-up fee of 4€. We used "Taler" as an experimental currency where each Taler was worth 0.50€. Subjects received an initial endowment of 8 Taler in each of parts I and II from which losses were subtracted and to which gains were added. Participants that made losses in both parts still kept their show-up fee, following standard procedures as implemented by Kagel and Levin (1986) and ILN. Sessions lasted on average 60-75 minutes and subjects earned on average 14.40€.

2.3 Formalizing the Impact of Cognitive Complexities

The primitive of our approach is the focus on the objective game characteristics rather than the internal processes of subjects' reasoning. We provide a brief formalization of the quantitative impact on behavior caused by the game complexities studied here. If two game situations $G \in \{G_0, G_1\}$ differ only in the need to engage in one particular cognitive process D, we propose to evaluate this complexity based on the difference it generates in behavior between these games. We describe behavior $s \in \mathcal{S}$ as a probability measure over the action space of G or as a statistic thereof. We define the distance between observed behavior s and a benchmark behavior such as equilibrium s^e as $\tilde{\mu}(s, s^e)$, where $\tilde{\mu}(\cdot, \cdot) : \mathcal{S} \times \mathcal{S} \mapsto \mathbb{R}$ is an appropriately chosen divergence or metric.[11]

[10] The experimental software was developed in z-Tree (Fischbacher, 2007). For recruitment, ORSEE was used (Greiner, 2004).

[11] In case the benchmark behavior or action spaces are different between G_0 and G_1, an appropriate normalization can assure comparability.

We define D's impact on behavior as

$$\Delta\tilde{\mu}(D; G_0) \equiv \tilde{\mu}(s(G_1), s^e) - \tilde{\mu}(s(G_0), s^e), \tag{2}$$

and can interpret D as follows. If the presence of D keeps behavior further away from equilibrium play, $\Delta\tilde{\mu}(D) > 0$, we call it a *cognitive bad.* The presence of a *cognitive good* results in $\Delta\tilde{\mu}(D) < 0$. Such a good can be viewed as resulting from a negative complexity like, potentially, repeated game play or the substitution of probabilities with frequencies in games with Bayesian reasoning (Gigerenzer and Hoffrage, 1995). For simplicity, we omit the dependence of D's impact on circumstances $(\cdot; G_0)$ when it is of minor importance.

Two activities D_1 and D_2 are related to each other depending on the difference between the joint effect and the sum of the individual effects. Define

$$\Delta^2\tilde{\mu}(D_1, D_2) \equiv \Delta\tilde{\mu}(D_1 \cup D_2) - \left(\Delta\tilde{\mu}(D_1) + \Delta\tilde{\mu}(D_2)\right), \tag{3}$$

where $D_1 \cup D_2$ indicates the need to engage in both cognitive processes. Two activities exhibit *cognitive diseconomies* if their joint effect is larger than their summed individual effects, $\Delta^2\tilde{\mu}(D_1, D_2) > 0$. They exhibit *cognitive economies* if this difference is negative. This definition adapts the idea of diseconomies of scope $\Delta^2 C$ of multi-input cost functions, $C(a_1, a_2) = C(a_1, 0) + C(0, a_2) + \Delta^2 C(a_1, a_2; 0)$.

The strategy space in our games is a subset of the metric space of the real numbers. We summarize the action distribution in terms of relative bids with the mean statistic and can resort to the simple Euclidean distance as metric. We normalize the distance between uninformed random play $\mu^u(s^u, s^e) = 1$ and equilibrium or optimal play $\mu^e(s^e, s^e) = 0$ to 1, accounting for the fact that benchmark behavior is not always the same. In particular, we use a very simple normalization

$$\mu(s, s^e) \equiv \left| \frac{\bar{b} - b^e}{\bar{b}^u - b^e} \right|, \tag{4}$$

where $\bar{b}$ is the average behavior, and b^e and $\bar{b}^u$ are equilibrium or optimal play and uninformed random play averages. In our games, $b^e_{\star H} = -8$, $b^e_{\star C} = -5.99$ and $\bar{b}^u = 0$.

For our study, we denote the activity of conditional reasoning as required in the auction game but not in the transformed game, as D_A. Based on our two belief manipulations, we distinguish different types of cognitive complexities in the context of belief formation. First, we denote as $D_H = D_B \cup D_{SU}$ the forming of beliefs about the opponent that is required in the human opponent settings but not in the computerized settings. This reflects the cognitive complexity of full belief formation. Second, letting subjects play against humans after computers in the $\star H_{\star\mathcal{C}}$ games enables us to identify whether subjects already have problems to form any basic belief D_B irrespective of the need to account for potentially diverse behavior of other players D_{SU} in the form of strategic uncertainty. While subjects face the problem of uncertainty about others' behavior in any human setting, they have to craft a first belief or scenario by themselves in the $\star H$ games whereas this activity D_B is provided in $\star H_{\star\mathcal{C}}$ by the experience with the computer.

Figure 6 illustrates how the game complexities in our design relate. Since overall three manipulations are implemented, each individual cognitive complexity can be measured with at least two game comparisons, reflecting that the magnitude of an effect depends on circumstances, G_0. In the results section, we will first analyze all depicted comparisons and finally use a regression analysis to precisely quantify each cognitive complexity, controlling for interaction effects and thus circumstances.

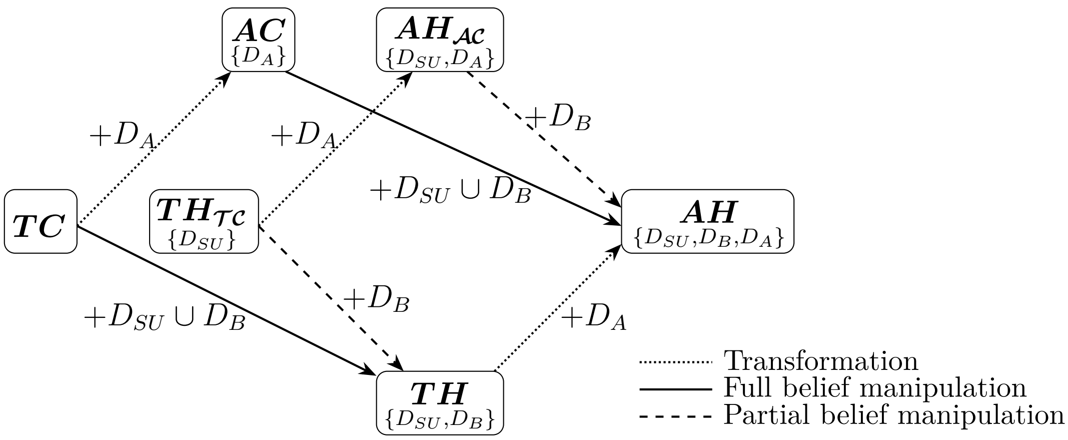


Figure 6: Differences between games with complexities added to TC in $\{\cdot\}$.

Our approach deliberately disregards the mechanisms behind subjects' inability to overcome a complexity D. We only assume that game complexity influences the distance of observed play to the equilibrium strategy. We remain agnostic as to whether it is the difficulty to form beliefs exactly as modeled in the level-k model or the obstacle of conditional reasoning as specifically modeled in CE. It turns out that in our specific games neither of the two predict differences between treatments. Appendix A.4 shows that except for the level-k model with truthful level-0, these models predict the equilibrium bid of $b^e = -8$.

2.4 Hypotheses

The large literature on belief formation and conditional reasoning undoubtedly suggests that the two processes analyzed in this paper are cognitive bads. Due to the intertwining of the two processes, they might exhibit cognitive diseconomies that distance behavior further from optimal play.

Hypothesis 1 (Conditional reasoning): *Due to the added need of conditional reasoning, subjects make higher bids and fall prey to the WC more frequently in the auction game compared to the transformed game, both with computer and human opponents as well as when facing human after computer opponents:* $\Delta\mu(D_A) > 0$.

Hypothesis 2a (Full belief formation) *Due to the added need of full belief formation, subjects make higher bids and fall prey to the WC more frequently in both games when playing against human opponents than when playing against computerized opponents:* $\Delta\mu(D_B \cup D_{SU}) > 0$.

Hypothesis 2b (Partial belief formation): *Due to the added need of forming a basic first belief, subjects make higher bids and fall prey to the WC more frequently with human opponents in both games if the game is played first compared to when it is played after the setting with computer opponents:* $\Delta\mu(D_B) > 0$.

Hypothesis 3 (Magnitudes, cognitive diseconomies): *The effects of* D_H *and* D_A *are different in magnitude:* $\Delta\mu(D_A) \neq \Delta\mu(D_H)$. *Similarly,* $\Delta\mu(D_A) \neq \Delta\mu(D_B)$. *Subjects make higher bids and fall prey to the WC more frequently when both* D_A *and* D_H *are present than predicted by* $\Delta\mu(D_A; TC)$ *and* $\Delta\mu(D_H; TC)$ *alone. In other words, we observe cognitive diseconomies* $\Delta^2\mu(D_A, D_H; TC) > 0$. *Weaker diseconomies are observed for* D_B *instead of* D_H.

3 Results

The following summary statistics and tests use the average bids and payoffs over the three periods of each specific game.[12] Only the percentage of winners incurring losses is calculated using the per-period information.

Since means and distributions only proxy for the plausibility of bids, we also report bids in four meaningful categories which furthermore can account for the fact that equilibrium bids are different between the settings with human and computer

[12] In the few cases in which we drop observations due to a signal realization below 46, the average is over 2 bids.

opponents. These categories are determined by whether bids can be a valid best response. In the H games, the important thresholds are at $b_i = -8, -5, -3$. The first category is the equilibrium strategy, bidding $b_i = -8$.[13] The next threshold is the best response to a naïve strategy, $b_j = 0$, which we round up from the precise value $b_i = -5.99$ to $b_i = -5$ because some subjects only bid integer values. Finally, bidding $b_i > -3$, that is $a_i > E[W^*|x_i, l]$, is a weakly dominated strategy. Intuitively, whenever j bids very high values ($b_j \geq 3$), no positive payoffs can be obtained, and any bid $b_i \leq b_j - 6$ is a best response. Whenever positive payoffs can be achieved for lower bids of j, there is always a strategy $b_i < -3$ that leads to higher expected payoffs than bidding above -3. Overall, we think that bids $b_i \in [-8, -5]$ represent plausible behavior. Bids $b_i \in (-5, -3]$ might be a best response but only to some forms of fairly implausible beliefs; bids above are weakly dominated. For the C games, a similar picture emerges in which we distinguish precise and approximate optimal behavior, $b_i = -5.99$ and $b_i \in (-5.99, -5]$, respectively, from non-optimal behavior $b_i < -5.99$ and $b_i > -5$.[14]

3.1 Conditional Reasoning (Hypothesis 1)

With respect to conditional reasoning and following the illustration of figure 6, we are mainly interested in three different comparisons between the auction and the transformed games ($\star H$, $\star C$, $\star H_{\star\mathcal{C}}$). For all three comparisons, a higher percentage of winners in the auction game face losses than in the transformed game: 61% do so in AH but only 32% in TH; 45% do so in AC but only 24% in TC. Finally, 52% do so in $AH_{\mathcal{AC}}$ but only 21% in $TH_{\mathcal{TC}}$.[15] These outcomes follow from bidding behavior illustrated in table 2. Average bids in T are significantly lower and thus closer to the equilibrium or optimal behavior compared to A, in $\star H$, $\star C$, and $\star H_{\star\mathcal{C}}$. The differences in payoffs are also significantly different irrespective of the

[13] Given the empirical distribution of subjects' behavior, equilibrium play is not a best response, but it is close. In AH, bidding $b_i = -7.97$ is the best response. In TH, bidding $b_i = -7.99$ is the best response.

[14] When performing between-treatment comparisons below, we will use Fisher's exact tests that only rely on the two categories: plausible vs. implausible play. First, comparing human and computer settings with four categories is not desirable due to different category boundaries. Second, for similar within-subject comparisons, the McNemar's test is used that only relies on binary categories. Importantly, using four categories for testing when this is feasible leads to very similar results, suggesting that our analysis is robust at least with respect to the number of categories used.

[15] When discussing the extent of the WC, we refer to actual probabilities with which winners face losses. Table 3 and Figures A.1-A.4 nonetheless show that very similar percentages emerge when looking instead at those who bid above the conditional item value: $b_i > -3$. Especially for AH, the extent of the WC would even be higher under the latter measure (72% vs. 61%): bidding above -3 may not lead to losses in case someone else bids even higher.

Table 2: Summary statistics.

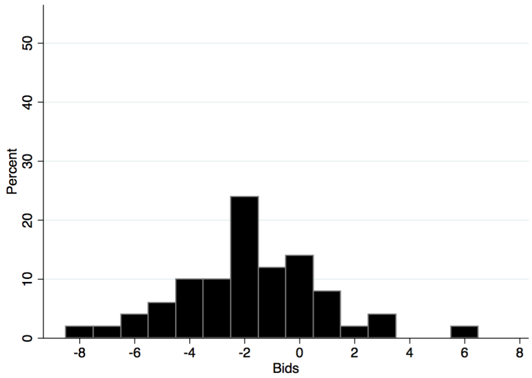
Means (Std. deviation)		A	T	Wilcoxon p-value
$\star H$		AH	TH	
	Bids	–1.80	–4.00	0.000
		(2.63)	(2.61)	
	Payoffs	–0.56	0.55	0.001
		(1.55)	(1.37)	
$\star C$		AC	TC	
	Bids	–2.83	–4.18	0.079
		(3.65)	(2.90)	
	Payoffs	–0.12	0.37	0.099
		(1.99)	(2.11)	
$\star H_{\star\mathcal{C}}$		$AH_{\mathcal{AC}}$	$TH_{\mathcal{TC}}$	
	Bids	–2.62	–4.64	0.024
		(4.15)	(2.83)	
	Payoffs	–0.57	0.82	0.003
		(2.46)	(1.56)	
$\star H$ vs. $\star C$ Wilcoxon p-value	Bids	0.022	0.323	
	Payoffs	0.033	0.434	
$\star H$ vs. $\star H_{\star\mathcal{C}}$ Wilcoxon p-value	Bids	0.166	0.173	
	Payoffs	0.303	0.116	

Notes: The last column and the last rows report two-sided p-values of Wilcoxon rank sum tests that evaluate whether the distribution of bids and payoffs is different between games/treatments. Noteworthy, the difference in equilibria biases against observing a difference when comparing $\star H$ (-8) vs. $\star C$ (-5.99).

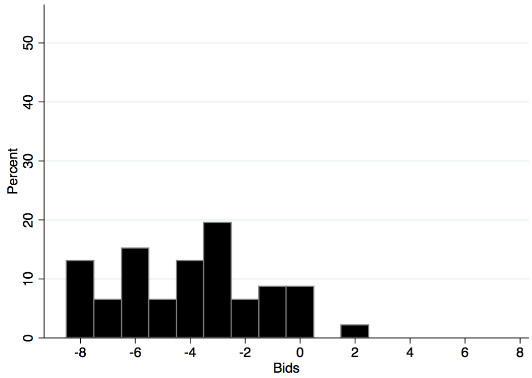
opponents. In A, subjects on average lose money while they gain in T.

Figure 7 reports subjects' bid distributions in the relevant games. The histograms in figure 7a and 7b reflect that subjects play lower bids more often in TH than they do in AH. Actually, the bidding behavior in AH gives the impression of normally distributed bids that do not reflect the equilibrium strategy of $b_i = -8$ at all, whereas bidding behavior in TH at least partially reflects that the equilibrium is the lowest possible bid. For $\star C$, figures 7c and 7d show that a larger number of subjects is able to find the exact equilibrium when strategic uncertainty as in $\star H$ is absent. Finally, figures 7e and 7f show a similar difference between A and T when subjects play against humans after playing against the computer, $\star H_{\star\mathcal{C}}$, although bids seem to be slightly more negative in both settings compared to $\star H$.

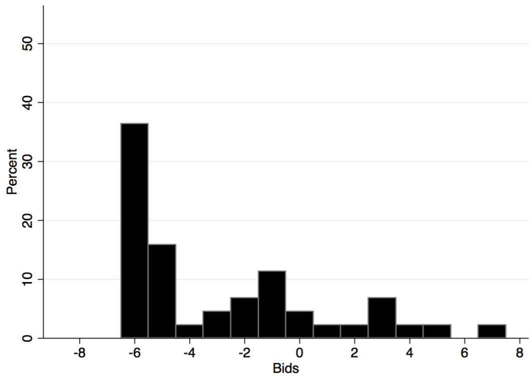
Table 3 shows data on plausible behavior. It reveals that 39% of subjects (18 of



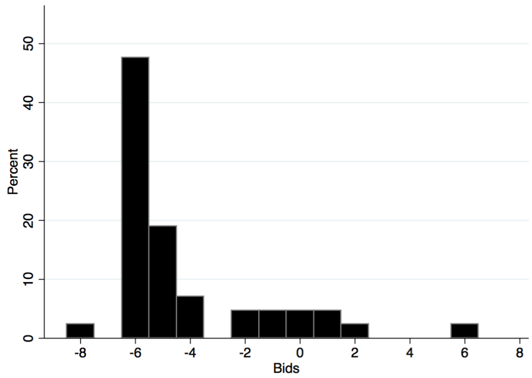
(a) AH, $N = 50$.



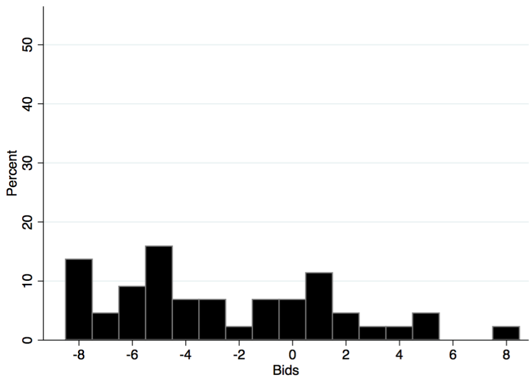
(b) TH, $N = 46$.



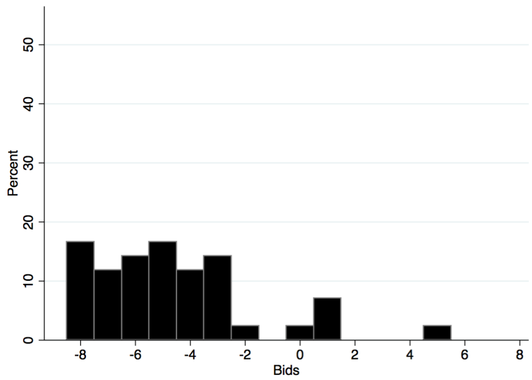
(c) AC, $N = 44$.



(d) TC, $N = 42$.



(e) $AH_{\mathcal{AC}}$, $N = 44$.



(f) $TH_{\mathcal{TC}}$, $N = 42$.

Figure 7: Histograms of bids.

46) bid plausibly in TH while only 12% (6 of 50) do so in AH (Fisher's exact test, $p = 0.004$).[16] Consistently, 57% (24 of 42) bid plausibly in $TH_{\mathcal{TC}}$ but only 39% (17 of 44) bid plausibly in $AH_{\mathcal{AC}}$ (Fisher's exact test, $p = 0.083$). Moreover, the precise or the approximate optimal action is played by 64% (27 of 46) in TC but only by 43% of subjects (19 of 44) in AC (Fisher's exact test, $p = 0.090$).[17] Hence, even if subjects exactly know how their opponents act, conditional reasoning still is a problem at least for some subjects.[18]

Table 3: Behavior by categories of plausible play (in bold).

	$[-8]$	$(-8,-5]$	$(-5,-3]$	$(-3,8]$	Total
AH	**0**	**6**	8	36	50
TH	**6**	**12**	12	16	46
$AH_{\mathcal{AC}}$	**1**	**16**	6	21	44
$TH_{\mathcal{TC}}$	**4**	**20**	9	9	42
	$[-8,-6]$	$[-5.99]$	$(-5.99,-5]$	$(-5,8]$	Total
AC	1	**12**	**7**	24	44
TC	1	**16**	**11**	14	42

Notes: All in the text reported tests of differences in plausibility are 2×2 tests of equality.

The analysis so far has focused on the six games illustrated in figure 6 and presented between-treatment comparisons. Our design, however, also allows within-subject comparisons with respect to H and C as illustrated in the bid transitions in table 4. Figures A.1 – A.4 graphically illustrate the individual data. Two important features are noteworthy. First, in $\mathcal{AH}$ (but also in $\mathcal{AC}$), 19 subjects play bids in the top-right cell, that is, higher than -3 in H and higher than -5 in C. This kind of bidding is less common in $\mathcal{TH}$ and $\mathcal{TC}$ where only 5 and 7 players do this. Second, in $\mathcal{AH}$, of those 27 subjects playing reasonably in C, 17 or 63% bid above -3 in H, a weakly dominated strategy. Only 11 out of 37 (30%) do this in $\mathcal{TH}$. This suggests that beyond the ability to best respond, the conditional reasoning increases the difficulty of belief formation. In AH compared to TH, relatively more subjects who are in C able to best respond fail to form adequate

[16] All reported tests in this paper are two-sided.

[17] This result speaks against the idea that potential differences in framing of the two games just lead to more cautious play in the transformed game. In the computer setting, more subjects seem to understand the game and make lower but not too low bids, $b_i < -5.99$.

[18] For completeness, we note that comparing $AC_{\mathcal{AH}}$ with $TC_{\mathcal{TH}}$ instead of AC with TC leads to even more significant results (bids, $p = 0.007$; payoffs, $p = 0.004$; plausible play, $p = 0.009$).

beliefs about human opponents and to best respond to them. Due to the change in the sequence, we do not observe such a difference in the $\mathcal{C}$ treatments.

Table 4: Bid transition by categories (Part I, plausible play in bold).

$b_i \in [\ldots]$	H				
C	$[-8]$	$(-8,-5]$	$(-5,-3]$	$(-3,8]$	Total
			$\mathcal{AH}$ treatment		
$(-5,8]$	**0**	**0**	4	19	23
$(-5.99,-5]$	**0**	**1**	**0**	**8**	**9**
$[-5.99]$	**0**	**5**	**4**	**9**	**18**
$[-8,-6]$	**0**	**0**	0	0	0
Total	**0**	**6**	8	36	50
			$\mathcal{TH}$ treatment		
$(-5,8]$	**0**	**1**	2	5	8
$(-5.99,-5]$	**2**	**2**	**5**	**4**	**13**
$[-5.99]$	**4**	**9**	**4**	**7**	**24**
$[-8,-6]$	**0**	**0**	1	0	1
Total	**6**	**12**	12	16	46
			$\mathcal{AC}$ treatment		
$(-5,8]$	**0**	**4**	1	19	24
$(-5.99,-5]$	**0**	**3**	**4**	**0**	**7**
$[-5.99]$	**0**	**9**	**1**	**2**	**12**
$[-8,-6]$	**1**	**0**	0	0	1
Total	**1**	**16**	6	21	44
			$\mathcal{TC}$ treatment		
$(-5,8]$	**0**	**3**	4	7	14
$(-5.99,-5]$	**1**	**10**	**0**	**0**	**11**
$[-5.99]$	**3**	**6**	**5**	**2**	**16**
$[-8,-6]$	**0**	**1**	0	0	1
Total	**4**	**20**	9	9	42

Clearly, results so far indicate that conditional reasoning is a cognitive bad as it distances behavior from optimal play, $\Delta\mu(D_A) > 0$. We relegate the discussion of the magnitudes and its comparisons across complexities to section 3.3 where we can base it on the regression results. Table A.1 on page 40 calculates the magnitudes for various effects and environments based on the average bids seen until now.

Result 1: For all three settings, $\star H$, $\star C$, and $\star H_{\star\mathcal{C}}$, we find that, with conditioning, subjects bid higher and are worse in avoiding the WC, $\Delta\mu(D_A) > 0$. Hence, we find evidence even in a CVA setting with human opponents that the difficulty of conditional reasoning is one reason behind the WC.

We find another consequence of the need to condition when we analyze subjects' behavior over the three periods of each game. When we test the equality of the distribution of bids in the first and the last period of each game, only 2 out of the 16 games show significant differences. Subjects bid significantly closer to the equilibrium in the third compared to the first period only when the transformed game is played as the first game (*TH*, p=0.001, and *TC*, p=0.067). Therefore, only without the need of conditional reasoning, subjects are able to improve their behavior even though they do not receive feedback.[19]

3.2 Belief Formation (Hypothesis 2)

With respect to full belief formation, comparing $\star H$ with $\star C$, we observe the following results: In *AH*, 61% of the auction winners face losses whereas only 43% do in AC. In *TH*, 32% of the winning subjects face losses whereas in TC only 24% do so. Table 2 shows that in the A games subjects bid significantly lower and make significantly higher profits in $\star C$. No statistical difference is observed for the T games. Note, however, that the difference in the optimal bid between C (-5.99) and H (-8) biases against observing a difference.

In contrast, measures of plausible play can be compared better, leading to a cleaner measure. Judging by the categories of table 3, 6 out of 50 subjects, or 12%, behave plausibly in AH while 19 out of 44, or 43%, do so in AC (Fisher's exact test, $p < 0.001$). In TH, 18 out of 46 subjects, or 39%, behave plausibly while 27 out of 42, or 64%, do so in AC (Fisher's exact test, $p = 0.011$).[20]

The strong impact of the removal of both strategic uncertainty, D_{SU}, and basic belief formation, D_B, may not be surprising. However, within-subject analyses of the $\mathcal{AH}$ and $\mathcal{TH}$ treatments in table 4 (figures A.1 and A.3) provide first evidence that strategic uncertainty alone may not be able to explain the differences between settings. In both cases, out of those respective 27 and 37 subjects that

[19]Our central results regarding conditional reasoning and belief formation remain in general robust to considering first or third period bids instead of mean bids, although differences are less pronounced as single period data is naturally more noisy. Appendix B.1 provides further details.

[20]For completeness, we note that these findings can be corroborated using within-subject data from the $\mathcal{AH}$ and $\mathcal{TH}$ treatments. Comparing AH with $AC_{\mathcal{AH}}$ instead of AC leads to: bids, $p <$ 0.001; payoffs, $p < 0.001$; plausible play, $p < 0.001$. Comparing TH with $TC_{\mathcal{TH}}$ instead of TC leads to: bids, $p = 0.020$; payoffs, $p = 0.184$; plausible play, $p < 0.001$. For testing plausible play, we use the McNemar's test that performs a similar test as the Fisher's exact test for matched data.

approximately best respond in C, still a substantial fraction of 17 and 11 players, respectively, plays a weakly dominated strategy in H. A potential explanation is that – beyond strategic uncertainty – subjects in both games have difficulties developing first beliefs to which they could apply their best response abilities. Without forming these beliefs, they end up bidding weakly dominated strategies, despite their general ability to best respond. The partial belief manipulation analyzes this idea further.

> **Result 2a:** We find that basic belief formation and strategic uncertainty provide additional obstacles for avoiding the WC both in the auction and in the transformed game, $\Delta\mu(D_B \cup D_{SU}) > 0$. However, strategic uncertainty alone may not be able to explain our results.[21]

Under partial belief formation, comparing $\star H_{\star\mathcal{C}}$ with $\star H$, 52% of subjects winning the auction when facing humans subsequently to computers in $AH_{\mathcal{AC}}$ face losses while 61% of subjects do so in AH. Moreover, 21% do so in $TH_{\mathcal{TC}}$ and 32% in TH.

Table 2 shows that bids differ in the expected direction between AH and $AH_{\mathcal{AC}}$, but this difference is not significant ($p = 0.166$). Importantly, table 3, however, shows that plausible bids below -5 are more frequent in $AH_{\mathcal{AC}}$ than in AH (Fisher's exact test, $p = 0.004$).

The within-subject analysis in table 4 (figure A.2) shows further that – just like in the $\mathcal{AH}$ treatment – numerous subjects place bids in the top-right cell in $\mathcal{AC}$ as well. More interestingly, in $\mathcal{AC}$, out of the 19 subjects approximately best responding in C, only 2 bid higher than -3 in H. As mentioned, in $\mathcal{AH}$, out of 27 that play a best response in C, 17 bid higher than -3 in H. Therefore, pairing the general ability to best respond with a little help in the belief formation – the computer providing a first basic belief – has a strong influence on the bids placed against human opponents.

The treatment $\mathcal{TC}$ indicates that this effect is not due to the learning of conditioning during the preceding play in C. Table 2 shows that the absolute difference in bids between TH and $TH_{\mathcal{TC}}$ is 0.64 with a p-value of 0.173, very similar to the $\mathcal{A}$ treatments.[22] The changes in the transition between C and H

[21] The partial belief manipulation discussed below shows that result 2a cannot exclusively be driven by the possibility that subjects experience a higher "joy of winning" with human opponents than with computer opponents.

[22] Due to the overall lower bidding in the $\mathcal{T}$ treatments, there is no significant difference between categories as depicted in table 4 (Fisher's exact test, $p = 0.134$). If we, however, only consider those subjects who at least approximately best respond, $b_i \in [-5.99, -5]$, in C, more subjects play plausibly in $TH_{\mathcal{TC}}$ than in TH (Fisher's exact test, $p = 0.056$).

(table 4 and figure A.4) are similar to the $\mathcal{A}$ treatments.[23]

> **Result 2b:** Although the observed difference in mean bids is not significant, playing first against computer opponents leads to significantly more plausible play against human opponents, showing that subjects already have problems to form a basic belief irrespective of strategic uncertainty, $\Delta\mu(D_B) > 0$.

3.3 Conditioning vs. Belief Formation (Hypothesis 3)

To conclude our analysis, we investigate which of the two complexities, the necessity to condition or the necessity to form beliefs, has a stronger impact on subjects' behavior and how they relate to each other.

We start by looking at conditional reasoning and *full* belief formation. Figure 8 shows the empirical cumulative distribution functions (CDF) of the first games in all four treatments, capturing full belief manipulation and the transformation (see figure 6). For an undistorted comparison, we adjust bids in C games for the fact that the optimal bid is different from the equilibrium bid against humans.[24] Note first that the leftmost distribution closest to equilibrium shows behavior in TC without either complexity. Then, no significant differences emerge when we compare playing against human opponents requiring belief formation, TH, to playing in an auction setting requiring conditional reasoning, AC (plausible play: 39% vs. 43%, $p = 0.831$; adjusted bids: -4.00 vs. -3.97; payoffs: 0.55 vs. -0.12, $p = 0.289$). Only a Kolmogorov-Smirnov test – testing for first-order stochastic dominance – suggests a difference in the underlying distributions, namely that in TH higher values are bid compared to AC (adjusted bids $p = 0.016$). The distribution of AH reflects clearly the behavior furthest from equilibrium.

In TC, without both complexities, 24% of winners face losses, 32% do so in TH with the belief formation problem, 39% with the conditioning problem in AC, and

[23] Unsurprisingly, playing against humans first does not help playing against the computer in $AC_{\mathcal{AH}}$ or $TC_{\mathcal{TH}}$. No significant differences between $AC_{\mathcal{AH}}$ and AC arise (bids, $p = 0.524$; payoffs, $p = 0.825$; plausible play, $p = 0.310$). The same is true for $TC_{\mathcal{TH}}$ compared to TC (bids, $p = 0.135$; payoffs, $p = 0.301$; plausible play, $p = 0.281$).

[24] This adjustment is done such that the optimal behavior in both settings is reflected by $\tilde{b} = -8$ and follows our normalization proposed in equation 4. Basically, for the computerized setting, we first normalize bids according to equation 4 using $b^e = -5.99$ and then map them back into [-8,8] as if we were inverting the normalization for human opponents. Noteworthy, not adjusting bids leads to very similar results as the significance level of non-parametric tests between TH and AC does not change (bids: -4.00 vs. -2.83, $p = 0.336$). Moreover, a Kolmogorov-Smirnov test with unadjusted bids is unable to detect a difference, which is even more in line with our general conclusion that there is no difference between conditional reasoning and belief formation.

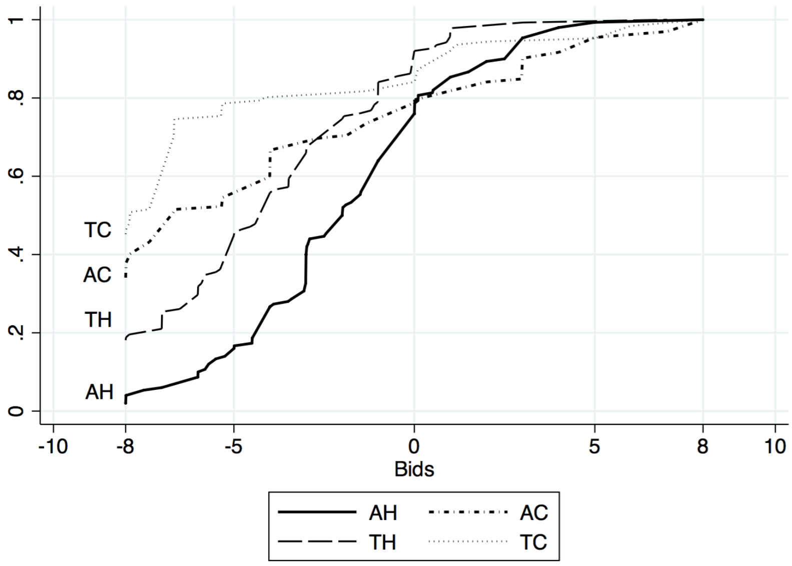


Figure 8: CDFs of subjects' adjusted bids: conditioning and full removal of belief formation

61% when facing both in *AH*. The difference between *TH* and *AC* is not significant according to a proportion test ($p = 0.399$).

Figure 9 alternatively shows the CDF's of bids in the four $\star H$ and $\star H_{\star\mathcal{C}}$ games used to analyze the *partial* belief formation. This time, the leftmost distribution closest to equilibrium shows behavior in $TH_{\mathcal{TC}}$ in which subjects already have to deal with strategic uncertainty, D_{SU}. In this setting, moving from $TH_{\mathcal{TC}}$ to TH captures forming a first belief, D_B, and moving from $TH_{\mathcal{TC}}$ to $AH_{\mathcal{AC}}$ captures conditional reasoning. Here, the measurement of both complexities already includes the interaction with strategic uncertainty. Interestingly, even in this partial setting, there is no significant difference between $AH_{\mathcal{AC}}$ and *TH* in plausible behavior or bids and only a marginally significant difference in payoffs (plausible play 39% vs. 34%, $p = 1.000$; bids: -4.00 vs. -2.62, $p = 0.148$; payoffs: 0.55 vs. -0.57, $p = 0.060$). Again, a Kolmogorov-Smirnov test suggests a difference in the underlying distributions ($p = 0.062$). This time, however, bidding in TH is lower than bidding in $AH_{\mathcal{AC}}$.[25]

In $TH_{\mathcal{TC}}$, 21% of winners face losses, 32% do so in *TH*, 52% do so when the conditioning problem in $AH_{\mathcal{AC}}$ is activated, and 61% when facing both conditional reasoning and belief formation in *AH*. The difference between *TH* and $AH_{\mathcal{AC}}$

[25]As noted earlier, having subjects play first in C seems to help those that are able to best respond, but it does not help those who have a more fundamental problem understanding the game. For this reason, the CDF of $AH_{\mathcal{AC}}$ is very similar to the CDF of the behavior in TH in the interval $[-8, -5]$. Afterwards, however, the former CDF approaches again the CDF of AH.

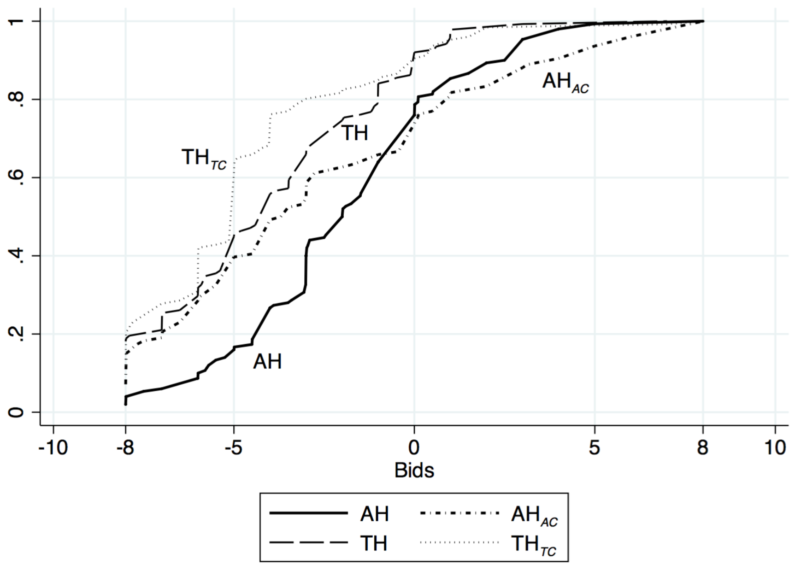


Figure 9: CDFs of subjects' bids: conditioning and partial removal of belief formation

is significant according to a proportion test ($p = 0.016$), highlighting that if we observe a difference in the partial manipulation at all, it is with respect to payoffs. Under this partial belief formation and thus in the context of strategic uncertainty, conditional reasoning increases the percentage points of subjects facing losses quite substantially (31 percentage points compared to 15 with full belief formation). Note, however, that beyond the pure effect of conditional reasoning, this also incorporates interactions with strategic uncertainty.

For a final overview, table 5 shows random-effects panel regressions in which the dependent variable is the bid. These regressions allow us to quantify the impact of the considered cognitive complexities $\Delta\mu(\cdot)$ while at the same time appropriately controlling for interaction effects and thus circumstances. All regressions include dummies that indicate the presence of the conditioning problem in auction games to calculate $\Delta\mu(D_A)$, the presence of the belief formation problem when playing against human opponents to calculate $\Delta\mu(D_H)$, and the interaction term of the two dummies, $\Delta^2\mu(D_A, D_H)$. Moreover, to additionally capture the partial belief formation, a dummy indicates whether subjects play against human opponents after playing against computer opponents, $-\Delta\mu(D_B)$. Additionally, an interaction of the latter dummy with the conditioning problem is added, $-\Delta^2\mu(D_A, D_B)$. While regressions 1, 3, and 5 only use part I data, regressions 2, 4, and 6 also include part II data. They additionally control for learning by including a part II-dummy, an interaction with the treatments $\mathcal{TC}/\mathcal{TH}$ and a dummy for the last

Table 5: Panel regression on bids

Variables	Bids		Adjusted bids		Normalized bids	
	Part I	Parts I&II	Part I	Parts I&II	Part I	Parts I&II
Related complexity	(1)	(2)	(3)	(4)	(5)	(6)
Auction games	1.49***	1.32***	1.89***	1.48***	0.24***	0.18***
$\Delta\mu(D_A)$	(0.46)	(0.44)	(0.61)	(0.53)	(0.08)	(0.07)
Human opponents	0.86**	0.10	2.37***	1.57***	0.30***	0.20***
$\Delta\mu(D_H)$	(0.37)	(0.29)	(0.41)	(0.33)	(0.05)	(0.04)
Auction × Human	0.63	1.03***	0.21	1.11***	0.03	0.14***
$\Delta^2\mu(D_A, D_H)$	(0.51)	(0.37)	(0.59)	(0.40)	(0.07)	(0.05)
Human after comp.	-1.18**	-0.54	-1.33**	-1.21***	-0.17**	-0.15***
$-\Delta\mu(D_B)$	(0.51)	(0.36)	(0.53)	(0.44)	(0.07)	(0.05)
Human a. comp. × Auction	0.01	-0.16	0.04	-0.13	0.00	-0.02
$-\Delta^2\mu(D_A, D_B)$	(0.71)	(0.42)	(0.72)	(0.42)	(0.09)	(0.05)
Learning - Part II		1.16***		1.11**		0.14**
		(0.44)		(0.54)		(0.07)
Learning × $\mathcal{TC}/\mathcal{TH}$		-2.56***		-3.04***		-0.38***
		(0.79)		(0.92)		(0.11)
Lastgame				0.68**		0.08**
				(0.29)		(0.04)
Constant	-4.61***	-4.38***	-6.04***	-5.67***	0.24***	0.29***
	(0.29)	(0.27)	(0.38)	(0.34)	(0.05)	(0.04)
N	364	728	364	728	364	728
Subjects	182	182	182	182	182	182
R^2 overall	.093	.053	.125	.083	.125	.083

Notes: Panel random-effects regressions. The dependent variable is bids. For specifications (3)-(4), bids have been adjusted for settings with computer opponents to assure consistency of equilibrium bids (see footnote 24). For specifications (5)-(6), bids are normalized (see footnote 26). Cluster-robust standard errors (subject level) are provided in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level.

game in the treatment. Regressions 3 and 4 adjust bids as before for the fact that the optimal bid against the computer is different from the equilibrium bid against humans, an effect which distortively dampens the effect of the human opponents in 1 and 2. Finally, regressions 5 and 6 present normalized bids and allow an easy quantification of the effects.[26]

Table 5 confirms that both complexities, conditioning and full belief formation, individually lead to higher bids, significantly so when we adjust for the difference of optimal bids between human and computer opponents or normalize bids (regressions 3-6). Differences between the two coefficients are not significant in regressions 1 and 3-6 (Z-Test, $p > 0.2$). Additionally, the interaction term always has a positive sign and is significant when we make use of all available data.[27] Moreover, providing

[26]Since the adjustment in (3) and (4) follows our normalization as proposed in equation 4, coefficients in (5) and (6) are effectively the same as those in (3) and (4) divided by 8.

[27]The results further support the idea that subjects bid lower in part II when they have played

a first basic belief by playing first against the computer significantly improves behavior.

Using all available data, effects can be easily quantified by looking at regression 6: the constant suggests that behavior without either complexity is relative close to the equilibrium bid of -8, $\mu(\bar{b}(TC), b^e) = 0.29$. As indicated by the dummy coefficients, both cognitive complexities deteriorate behavior by $\Delta\mu(D_A; TC) = 0.18$ and $\Delta\mu(D_H; TC) = 0.20$, respectively. Moreover, the joint effect intensifies this deviation because $\Delta^2\mu(D_A, D_H; TC) = 0.14$. Hence, there is evidence that the presence of both problems deteriorates subjects' play beyond the two individual effects. This reflects the idea that full belief formation and conditioning exhibit cognitive diseconomies that reinforce the individual problems. All three effects lead to behavior in AH that is fairly close to uninformed random behavior $\mu(\bar{b}(AH), b^e) = 0.81$, leading to a total effect of $\Delta\mu(D_A \cup D_H; TC) = 0.52$.

Similar results emerge for the partial belief formation. Naturally, the process of finding a first belief is less complex than full belief formation, suggesting that a weaker effect should be observed. Reflecting our results so far, the problem of finding a first basic belief, irrespective of strategic uncertainty, is still substantial: $\Delta\mu(D_B; TH_{\mathcal{TC}}) = 0.15$.[28] As expected, cognitive diseconomies between conditional reasoning and finding a first belief are smaller. They feature a non-significant value of $\Delta\mu^2(D_A, D_B; TH_{\mathcal{TC}}) = 0.02$.

Result 3: Conditional reasoning is as high an obstacle to optimal play in an auction context as is belief formation, $\Delta\mu(D_A) = \Delta\mu(D_H)$ and $\Delta\mu(D_A) = \Delta\mu(D_B)$. For partial belief formation we find insignificant diseconomies. Overall, however, there is significant evidence that the interaction of the two complexities intensifies the individual effects, $\Delta^2\mu(D_A, D_H) > 0$.

the transformed games in part I ($\mathcal{TC}/\mathcal{TH}$) but not the auction games. Subjects' performance deteriorates in the very last game of the experiment, potentially due to exhaustion or loosened self-restraint. Part II results are in line with the more detailed analysis in appendix B.1.

[28]Noteworthy, the regression also allows us to calculate $\Delta\mu(D_A; TH_{\mathcal{TC}}) = 0.30$, which is, however, not a pure conditional reasoning effect since it incorporates interactions with strategic uncertainty. As shown in figure 6, the starting point for the partial belief manipulation is $TH_{\mathcal{TC}}$. This starting point can be calculated via *Constant + Human opponents + Human after comp.*, resulting in $\mu(\bar{b}(TH_{\mathcal{TC}}), s^e) = 0.34$. Moreover, the transition to $AH_{\mathcal{AC}}$ can be calculated by *Auction games + Auction × Human + Human a. comp. × Auction*, resulting in $\Delta\mu(D_A; TH_{\mathcal{TC}}) = 0.30$.

3.4 Discussion

Most of our analysis is possible thanks to the transformation of the auction game that removes the need to condition. However, this transformation also removes private information from the auction and establishes common knowledge of the possible values. Subjects thus never form higher-order beliefs about players with other information. While from a theoretical perspective this is clearly not a conditioning manipulation that leaves everything else the same, there are various empirical arguments that convince us that the only behaviorally relevant change is in the need to condition.

First, we see that many subjects in the auction game bid weakly dominated strategies and hence a majority of subjects does not form beliefs at all. These subjects surely do not differentiate between opponents with different signals. In a pilot study, we saw that the few subjects who indeed form beliefs and deliberate about their opponent's behavior do so without differentiating the two possible values of the signal.[29] Relatedly, in the computer treatments, the games only differ in the need to condition and yield similar differences as in the human opponent setting.

Second, notably, the effect of conditional reasoning $\Delta\mu(D_A)$ is quantified based on the comparison between these computer treatments. Moreover, the belief formation effect $\Delta\mu(D_H)$ is quantified by comparing human and computerized opponents in the transformed game. Thus, only the interaction effect $\Delta^2\mu(D_A, D_B)$ involves the auction game with human opponents. The diseconomies between conditional reasoning and belief formation might be overestimated if the mere possibility of higher-order beliefs in the auction game makes forming beliefs – even those that do not involve higher-order beliefs – in general more difficult. Evidence from the partial belief manipulation does not support this worry. Providing a simple first belief – without higher-order considerations – leads to a similar improvement in the auction as in the transformed game. If possible higher-order beliefs made belief formation more difficult in general, one would expect the partial belief formation to have a smaller effect in the auction game.

Third, in the range of signals considered in our data analysis, the equilibrium consists of strategies of constant relative bidding. In our experiments, subjects indeed bid in accordance with this feature irrespective of the absolute signal

[29] We implemented the auction game with a communication design similar to Burchardi and Penczynski (2014). In this setting, teams of two players communicate about the bidding decision in a way that subjects have an incentive to share their reasoning about the game.

realization.[30] In equilibrium and empirically, there is thus no reason to differentiate beliefs with respect to the signal value.

Fourth, despite our efforts to frame the games similarly, one might be concerned that differences in the games' framing could explain the observed behavioral differences. Importantly, any framing explanation must be valid for different types of players. After all, we do not only observe differences in play of weakly dominated strategies but also observe a sharp difference in plausible play and even equilibrium play. Assuming e.g. that confused subjects are more likely to anchor their decision differently between the two games (signal vs. lower item value) does not explain why many of those players become sophisticated and play the equilibrium strategy in the transformed game.

Fifth, while it is in principle possible to implement the transformed game as a fully strategically equivalent game, this is very complicated for subjects since instructions would involve rules in terms of both absolute and relative bids.[31] Then, subjects might not approach such a fully equivalent game in terms of the described rules but in terms of the intuitive standard rules of an auction. An advantage of our transformation is the generation of a distinct setting that is not perceived as a standard first price-auction, also because it lacks the standard signal structure.

Finally, one could manipulate instructions such that they explicitly explain the conditioning problem without manipulating the actual auction game. It is, however, difficult to provide instructions that explain conditioning without influencing sophistication in terms of belief formation.

Our transformation requires as a starting point an auction game that is simplified compared to more standard CVAs. We restrict the number of subjects to two and let binary signals be drawn without replacement. While we expect that belief formation and conditional reasoning continue to matter similarly in more typical auctions as both activities likewise remain indispensable to reach a best response in more complex auctions, it is an open question what exactly the impact and

[30] When regressing the relative bids on absolute signals or on the mean value of the item for each of the four games, we only observe a significant positive effect for the transformed game with computer opponents. For the same game with human opponents and more importantly for both auction game settings, positive and negative coefficients arise and are always insignificant.

[31] Such a game would use the standard signal structure but replace the auction rule with rules set in terms of relative bids like in the transformed game. It follows that the description of the game setting would be in absolute bids, whereas the rules would use a relative perspective. Finally, profit calculations would again have to rely on absolute bids. Implementing and describing these changes of perspective would be very cumbersome and also constitute a major difference to the intuitive standard auction. A change of behavior would not be unambiguously attributable to the need of conditioning or to this change. Introducing common knowledge about the commodity's values allows us, however, to avoid a change between relative and absolute bids in the instructions.

interaction of added complexities such as a larger number of players or a richer state space would be. To which extent is a richer state space a cognitive bad? Does it exhibit cognitive diseconomies with conditional reasoning? If answers to these questions were known, combining such elements in an extended framework of cognitive complexities could inform expectations for extensions of auction games as well as predictions in a large number of other games.

Focusing on conditional reasoning, our transformation can potentially be applied to other games and environments. In the strategic voting literature, players are conditioning on being pivotal in a jury decision (Feddersen and Pesendorfer, 1998; Guarnaschelli, McKelvey, and Palfrey, 2000). Using a computer experiment, Esponda and Vespa (2014) find that the cognitive difficulty of this operation might stand in the way of strategic voting. An experiment based on a transformation of the kind presented here could verify these results in the original voting situation with human opponents.

After all, one might be tempted to turn to the behavioral models with our data. Recall that both the CE model as well as the level-k model with uniform level-0 distribution applied to our setting predict the Nash equilibrium behavior $b = -8$ (see appendix A.4). A level-k model with truthful level-0 play rationalizes behavior by attributing 72% of players to level-0 types in the AH game. Only the transformed games exhibit the standard hump-shaped level-k distribution and TC features a reasonable level average above 1.02. For this particular model, the observed difficulty of conditioning as well as the interaction between conditioning and belief formation might imply that higher levels are generally more difficult to reach and lower averages are to be expected. These potential dependencies highlight the value of considering complexities of a game and investigating their impact on behavior. Thus, our analysis can meaningfully complement studies that investigate particular models of reasoning such as Crawford and Iriberri (2007).

4 Conclusion

This study jointly analyzes two cognitive complexities associated with the winner's curse: conditional reasoning and belief formation. First, we transform a common-value first-price auction in a way that subjects do not need to condition on hypothetical future events. Second, we remove the need to form beliefs by letting subjects play either against naïve computer opponents or against human opponents subsequent to play against the naïve computer.

We provide a simple formalization of the impact of cognitive complexities on game play and can state the results as follows. Both activities, conditional reasoning and belief formation, constitute *cognitive bads* that significantly impair subjects' game play to a similar extent. Although their individual impact is limited, in combination they lead to widespread implausible behavior, exhibiting *cognitive diseconomies* as they interact and reinforce each other. Hence, adding the obstacle of conditional reasoning to the problem of belief formation – as it is done in many auctions – results in an extreme case of game-dependent sophistication. Our detailed experimental analysis allows us to reconcile ILN's critique of belief-based models with the numerous results in favor of them from other domains.

In our view, the focus on the elementary cognitive complexities is a useful complementary approach to the more common focus on behavioral models. Rather than explaining behavior, a better understanding of games' objective cognitive complexities and their effects could particularly improve the prediction across games. Investigating a wide range of games from this perspective – even in a meta-analysis of existing data – might be an insightful exercise for future research.

References

Avery, C. and J. H. Kagel (1997). Second-price auctions with asymmetric payoffs: An experimental investigation. *Journal of Economics & Management Strategy 6(3)*, 573–603.

Bazerman, M. H. and W. F. Samuelson (1983). I won the auction but don't want the prize. *Journal of Conflict Resolution 27*, 618–634.

Brandts, J. and G. Charness (2011). The strategy versus the direct-response method: a first survey of experimental comparisons. *Experimental Economics 14*(3), 375–398.

Brocas, I., J. D. Carrillo, S. W. Wang, and C. F. Camerer (2014). Imperfect choice or imperfect attention? understanding strategic thinking in private information games. *The Review of Economic Studies 81*(3), 944–970.

Burchardi, K. B. and S. P. Penczynski (2014). Out of your mind: Eliciting individual reasoning in one shot games. *Games and Economic Behavior 84*(0), 39–57.

Camerer, C., S. Nunnari, and T. R. Palfrey (2015). Quantal response and nonequilibrium beliefs explain overbidding in maximum-value auctions. Working paper.

Capen, E. C., R. V. Clapp, and W. M. Campbell (1971). Competitive bidding in high-risk situations. *Journal of petroleum technology 23*(06), 641–653.

Charness, G. and D. Levin (2009). The origin of the winner's curse: A laboratory study. *American Economic Journal, Microeconomics 1(1)*, 207–236.

Charness, G., D. Levin, and D. Schmeidler (2014). A generalized winner's curse: An experimental investigation of complexity and adverse selection.

Chou, E., M. McConnell, R. Nagel, and C. R. Plott (2009). The control of game form recognition in experiments: Understanding dominant strategy failures in a simple two person "guessing" game. *Experimental Economics 12*(2), 159–179.

Costa-Gomes, M. A. and M. Shimoji (2015). A comment on "can relaxation of beliefs rationalize the winner's curse?: An experimental study". *Econometrica 83*(1), 375–383.

Crawford, V. P., M. A. Costa-Gomes, and N. Iriberri (2013). Structural models of nonequilibrium strategic thinking: Theory, evidence, and applications. *Journal of Economic Literature 51*(1), 5–62.

Crawford, V. P. and N. Iriberri (2007). Level-k auctions: Can a nonequilibrium model of strategic thinking explain the winner's curse and overbidding in private-value auctions? *Econometrica 75*(6), 1721–1770.

Esponda, I. (2008). Behavioral equilibrium in economies with adverse selection. *The American Economic Review 98*(4), 1269–1291.

Esponda, I. and E. Vespa (2014). Hypothetical thinking and information extraction in the laboratory. *American Economic Journal: Microeconomics 6*(4), 180–202.

Eyster, E. and M. Rabin (2005). Cursed equilibrium. *Econometrica 73(5)*, 1623–1672.

Feddersen, T. and W. Pesendorfer (1998). Convicting the innocent: The inferiority of unanimous jury verdicts under strategic voting. *American Political Science Review*, 23–35.

Fischbacher, U. (2007). z-Tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics 10(2)*, 171–178.

Gigerenzer, G. and U. Hoffrage (1995). How to improve bayesian reasoning without instruction: frequency formats. *Psychological review 102*(4), 684.

Glazer, J. and A. Rubinstein (2004). On optimal rules of persuasion. *Econometrica 72*(6), 1715–1736.

Goeree, J. K. and T. Offerman (2002). Efficiency in auctions and public information in common values: An experimental study. *American Economic Review 92(3)*, 347–361.

Greiner, B. (2004). An online recruitment system for economic experiements. In K. Kremer and V. Macho (Eds.), *Forschung und wissenschaftliches Rechnen 2003. GWDG Bericht 63.* 79–93.

Grosskopf, B., Y. Bereby-Meyer, and M. Bazerman (2007). On the robustness of the winner's curse phenomenon. *Theory and Decision 63*, 389–418.

Guarnaschelli, S., R. D. McKelvey, and T. R. Palfrey (2000). An experimental study of jury decision rules. *American Political Science Review*, 407–423.

Ivanov, A., D. Levin, and M. Niederle (2010). Can relaxation of beliefs rationalize the winner's curse?: An experimental study. *Econometrica 78(4)*, 1435–1452.

Jehiel, P. (2005). Analogy-based expectation equilibrium. *Journal of Economic Theory 123*(2), 81 – 104.

Jehiel, P. and F. Koessler (2008). Revisiting games of incomplete information with analogy-based expectations. *Games and Economic Behavior 62*(2), 533–557.

Kagel, J. H. and D. Levin (1986). The winner's curse and public information in common value auctions. *American Economic Review 76(5)*, 894–920.

Kagel, J. H. and D. Levin (2002). Bidding in common-value auctions: A survey of experimental research. *Common Value Auctions and the Winner's Curse 1*, 1–84.

Levin, D., J. Peck, and A. Ivanov (2016). Separating bayesian updating from non-probabilistic reasoning: An experimental investigation. *American Economic Journal: Microeconomics 8*(2), 39–60.

Levin, D. and J. P. Reiss (2012). Could we overcome the winner's curse by (behavioral) auction design? *Mimeo*.

Lind, B. and C. Plott (1991). The winner's curse: Experiments with buyers and sellers. *American Economic Review 81(1)*, 335–346.

Louis, P. (2015). The barrel of apples game: Contingent thinking, inference from others' actions, and strategic heterogeneity.

McKelvey, R. D. and T. R. Palfrey (1995). Quantal response equilibria for normal form games. *Games and Economic Behavior 10*(1), 6–38.

Nagel, R. (1995). Unraveling in guessing games: An experimental study. *American Economic Review 85*(5), 1313–1326.

Nagel, R. and F. F. Tang (1998). Experimental results on the centipede game in normal form: an investigation on learning. *Journal of Mathematical Psychology 42*(2), 356–384.

Ngangoue, K. and G. Weizsäcker (2015). Learning from unrealized versus realized prices.

Osborne, M. J. and A. Rubinstein (1994). *A Course in Game Theory*. MIT Press.

Roll, R. (1986). The hubris hypothesis of corporate takeovers. *Journal of business*, 197–216.

Stahl, D. O. and P. W. Wilson (1995). On players' models of other players: Theory and experimental evidence. *Games and Economic Behavior 10*(1), 218–254.

Tversky, A. and D. Kahneman (1986). Rational choice and the framing of decisions. *The Journal of Business 59*(4), pp. S251–S278.

A Appendix

A.1 Figures: Bid Transitions

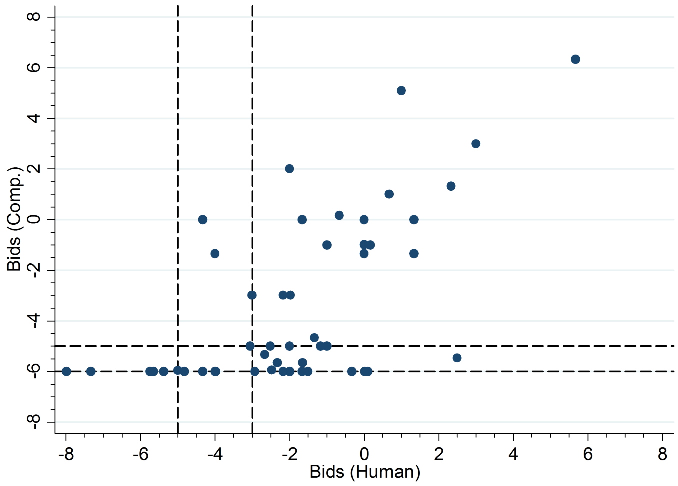


Figure A.1: $\mathcal{AH}$ treatment - bid transition (Part I), $N = 50$.

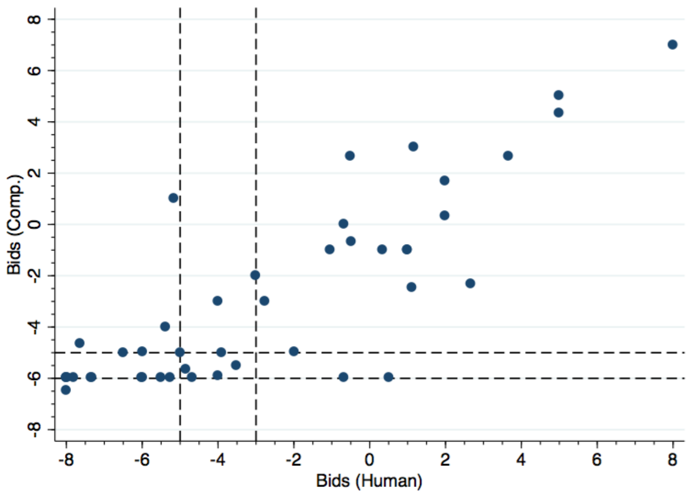


Figure A.2: $\mathcal{AC}$ treatment - bid transition (Part I), $N = 44$.

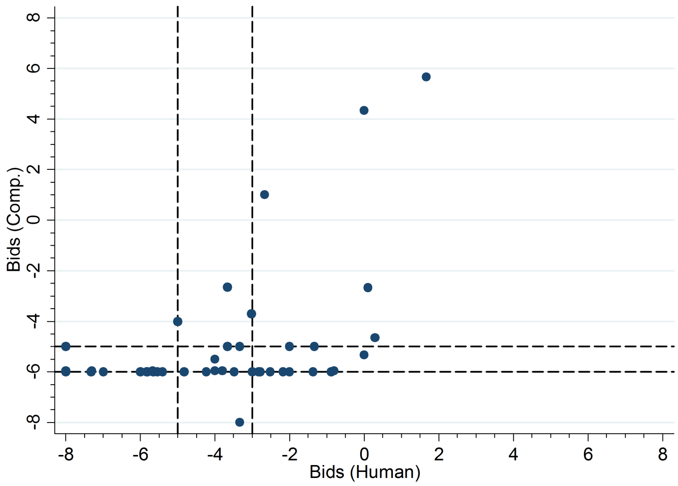


Figure A.3: $\mathcal{TH}$ treatment - bid transition (Part I), $N = 46$

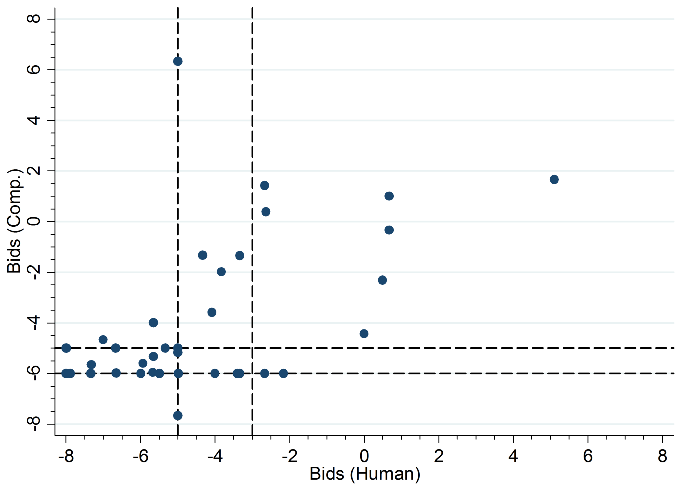


Figure A.4: $\mathcal{TC}$ treatment - bid transition (Part I), $N = 42$.

A.2 $\Delta\mu$ Calculation

Adj. Av.	$\mu(\bar{b}(\cdot), b^e)$	Adj. Av.	$\mu(\bar{b}(\cdot), b^e)$		
AH		TH		$\Delta\mu(D_A; TH)$	
-1.80	0.775	-4.00	0.500	0.275	
$AH_{\mathcal{AC}}$		$TH_{\mathcal{TC}}$		$\Delta\mu(D_A; TH_{\mathcal{TC}})$	
-2.62	0.672	-4.64	0.420	0.253	
AC		TC		$\Delta\mu(D_A; TC)$	
-3.97	0.504	-5.56	0.306	0.198	
	$\Delta\mu(D_B; AH_{\mathcal{AC}})$		$\Delta\mu(D_B; TH_{\mathcal{TC}})$	$\Delta\mu(D_A \cup D_B; TH_{\mathcal{TC}})$	$\Delta^2\mu(D_A \cup D_B; TH_{\mathcal{TC}})$
	0.103		0.080	0.355	0.023
	$\Delta\mu(D_H; AC)$		$\Delta\mu(D_H; TC)$	$\Delta\mu(D_A \cup D_H; TC)$	$\Delta^2\mu(D_A \cup D_H; TC)$
	0.271		0.194	0.469	0.077

Table A.1: $\Delta\mu(\cdot)$ and $\Delta^2\mu(\cdot)$ calculated for Part I adjusted averages.

Table A.1 illustrates how $\mu(\cdot), \Delta\mu(\cdot)$ and $\Delta^2\mu(\cdot)$ can be calculated using the mean values of bids in different games. Bids in C games are adjusted as described in footnote 24. In the main text, we provide calculations for these measures using the regression analysis of table 5. The regression analysis provides a unifying framework that allows to quantify the impact of our cognitive complexities and their interaction using all available data and not only part I data as in table A.1. Moreover, in the regression the significance of different effects can also be easily verified.

A.3 Proof of Proposition 1

In the auction game, particularly informative signals close to the boundary of the item's value may influence the optimal strategy. Intuitively, these changes result from the information obtained about the value of the item. A signal within 3 units of the lower boundary implies that the true value is the higher one, thus increasing incentives to bid more for the item. However, the influence of this change of strategy through higher order beliefs vanishes quickly due to the discrete signals and their fixed distance of 6 in combination with the limited action space, as we will be outlined below in detail.[32] For signals $x_i \in [46, 228]$, bidding -8 is optimal, as will be shown next. Notably, a signal within 3 units of the upper boundary implies that the true value can only be the lower one. There is thus no incentive to change the equilibrium strategy of bidding $b = -8$.

[32] In the original setup of Kagel and Levin (1986), signal noise follows a continuous, uniform distribution and actions are unconstrained. While the magnitude of the boundary effect quickly decreases, it never fully vanishes.

Proof. *Equilibrium.* We will first focus on signals $x_i \in [46, 228]$ for which higher-order beliefs do not influence optimal behavior. To analyze optimal behavior in both the auction game and the transformed game, consider the best response function to the opponent's bid b_j. When abstracting from boundary signals and assuming that players bid type-independently, these best response functions describe the same optimal behavior for both games.[33] If player j bids high values, $b_j \in [3, 8]$, it is optimal for player i to never win the auction in either game. The reason is that in this case, winning the auction would result in (weak) losses for sure in the auction game because the opponent is already bidding at least the commodity's value, even when she has received the lower signal. Analogously in the transformed game, the opponents is already bidding at least the higher value W_h^*. Hence, the best response is to bid anything that is relatively below the opponent's bid by at least 6 units, $BR(b_j) \in [-8, b_j - 6]$.

If player j bids values $b_j \in [-8, 3)$, it is optimal for player i to relatively underbid the opponent by slightly less than 6 points, making sure that he only wins the auction when he has received the higher signal or with 50% chance ("win in l"). Hence, the best response function is $BR(b_j) = b_j - 6 + \epsilon$. By construction, $b \in [-8, 8]$, player j cannot bid low enough to cause a best response of overbidding by at least 6 points and thus always winning the auction ("win in $\{l, h\}$"). Only if $b_j \leq -15$ was possible, the best response would be $BR(b_j) = b_j + 6$ since it would be more profitable to always win the auction than to only "win in l".

With the best responses being either to underbid by at least 6 or by nearly 6, the unique equilibrium for both players is to bid $b^e = b_i = b_j = -8$ in the transformed game. Similarly, any Nash equilibrium bid function takes the value $b^* = -8$ for signals $x \in [46, 228]$ (see discussion of boundaries below). Players then only win the auction when the lower item value realizes ("win in l"), leading to an expected payoff of $Eu_i = \frac{1}{2}(-3 - b_i) = 2.5$. If player i, however, deviated to "win in $\{l, h\}$", bidding $b_i = b_j + 6 = -2$, he would receive an expected payoff of only $Eu_i = \frac{1}{2}(-3 - b_i) + \frac{1}{2}(+3 - b_i) = \frac{1}{2}(-1 + 5) = 2$, showing that bidding -8 is an equilibrium.

Additionally, any equilibrium bid function exclusively takes the value -8 for signals $x \in [46, 228]$ since subjects always have incentives to deviate from any pair of strategies in which not both subjects bid $b_i = b_j = -8$. When both players bid higher values than -8, at least one player has an incentive to underbid the other player because, as outlined before, best responses are either underbidding by at least 6 or nearly 6 (if such an underbidding is possible). These underbidding

[33] We show below that incentives for type-dependent bidding only exist near the boundary.

incentives only vanish when no underbidding is possible anymore and subjects bid -8. If only one player bids more than -8, this player has an incentive to also bid -8 because of the outlined best response functions. These arguments also imply the uniqueness of the equilibrium in the transformed game.

Boundaries. In order to analyze whether the optimal strategies at the boundary influence strategies for central-value signals, we consider five player types. Player 5 receives a signal $x^5 \in [46, 54)$. His strategy might be influenced by his potential opponent with the lower signal: player 4, who receives the signal $x^4 = x^5 - 6, x^4 \in [40, 46)$. But player 4's strategy might of course be influenced by player 3 ($x^3 = x^4 - 6, x^3 \in [34, 40)$) whose strategy might be influenced by player 2 ($x^2 = x^3 - 6, x^2 \in [28, 34)$) and finally also by player 1 ($x^1 = x^2 - 6, x^1 \in [22, 28)$).

Player 1 receives a signal $x^1 \in [22, 28)$ from which he can infer that the commodity's real value is above his own signal. For this reason, player 1 cannot make any profits from bidding -8. Instead player 1 tries to overbid[34] player 2. But importantly, player 1 bids at most $b^1 = +3$ because otherwise he would lose money because of overbidding the commodity's value $x^1 + 3$. Hence, in equilibrium, player 2 will bid $b^2 \geq -3.01$ because any bid below would provide player 1 with an overbidding incentive that would lead player 2 to adjust his bid upwards. Additionally, player 2 cannot bid more than $b^2 = 0$ because higher bids would lead to negative expected payoffs. Because of these incentives of player 2, in equilibrium, player 3 can ensure himself an expected payoff of at least $Eu_i = 1.495$ by bidding $b^3 = -5.99$. If player 3 follows this strategy, player 2 cannot gain money by winning the auction, and, hence, player 2 will not overbid the player 3 and bids $b^2 = -3$ to avoid losses. This, however, provides an incentive for player 3 to bid less than -5.99, which in turn provides an incentive for player 2 to overbid the third player and these overbidding incentives only fully vanish when player 3 bids -5.99 again. Because of this circular incentive structure, in equilibrium, player 2 and player 3 will mix strategies. We do not fully characterize the exact mixed strategy equilibrium here, because it is sufficient for our purpose to show that players will not bid in certain intervals.[35]

As outlined before, for player 2, strategies above 0 cannot be part of an equilibrium. Hence player 3 can ensure himself a payoff of at least $Eu_i = 1.495$ by bidding -5.99. Importantly, strategies that are part of a mixed strategy equilibrium

[34] More precisely, due to the rule we implement concerning equal bids, overbidding in this context means that player 1 only has to bid exactly player 2's absolute bid in order win the auction.

[35] The strategy space in our experiment is finite because participants have to round their bids to the cent-level. But for finite strategy spaces we know that there always exists an equilibrium.

must lead to a higher payoff than strategies that are not part of this equilibrium. Hence, bidding $b^3 \in (-5.99, -2)$ cannot be part of a mixed strategy equilibrium because it leads to lower payoffs than bidding -5.99, independent of how player 2 exactly mixes pure strategies below $b^2 = 0$. Bidding $b^3 \in [-8, -5.99)$ could in principle lead to the same payoff (or even a higher payoff) as bidding -5.99 because the commodity's real value is underbid by a larger amount. The same is true for bidding $b^3 \in [-2, -1.50]$ because player 3 might overbid player 4 with these bids. By bidding above -1.5, player 3 might still overbid player 4, but the (maximal) payoff ($Eu_i = 1.49$) resulting from these bids is lower than the payoff of bidding -5.99. Bearing these considerations in mind, player 4 could always avoid to be overbid by player 3 by bidding $b^4 = -7.49$ and ensuring himself a payoff of $Eu^4 = 2.245$. Because player 3, however, does not bid -5.99 as a pure strategy but possibly also mixes strategies over $[-8, -5.99]$ and $[-2, -1.50]$, player 4 potentially mixes strategies over $-8 \leq b^4 \leq -7.49$. Importantly, bidding above -7.49 cannot be part of an equilibrium because then payoffs are lower than $Eu^4 = 2.245$. Especially overbidding player 5 even when this player is bidding $b^5 = -8$ would only lead to an expected payoff of $Eu^4 = 2.0$. For this reason, the influence on strategies of boundary-signals ends at player 5: This player and all players with higher signals than player 5 will bid -8 since their lower-signal opponents do not have an incentive to overbid them. In other words, for any signal $x \in [46, 228]$, any Nash equilibrium relative bid function takes the value $b^*(x) = -8$.

Additionally, at the higher boundary of the commodity's value space, no problems occur: A player receiving the signal $x^{high} \in (222, 228]$ knows that the commodity's real value is below his own signal. Hence, he has to underbid his opponent who has a lower signal in order to earn money. But this does not lead to a change in equilibrium bid function because in case the opponent bids -8, the player with x^{high} also just bids -8 and has no incentive to deviate. ■

A.4 Behavioral Models

A.4.1 Cursed Equilibrium

CE models a limited ability to infer about types from actions. Therefore, in many games, a type-dependent action space prevents a meaningful application of CE (Eyster and Rabin, 2005). In the following, we propose to discuss it in our context by averaging strategies in the space of possible absolute bids. Due to the symmetry of our setup around a player's signal, this approach should be true to the original idea of CE.

The prediction of full cursedness in our auction game is $b_i^{CE} = -8$, the same as in the transformed game and as the Nash equilibrium prediction. The intuition behind the equilibrium is the following: Player i with signal x_i faces an opponent with signal $x_j = x_i - 6$ or $x_j = x_i + 6$. Being fully cursed, he thinks that *both* potential opponent types bid $a_j = x_i - 6 + b_j$ or $a_j = x_i + 6 + b_j$ with 50% each. Bidding $b_i = -8$ in response to $b_j = -8$ yields an expected payoff of $Eu_i = 4$ (win in l), whereas $b_i = -1.99$ would only result in $Eu_i = 1.99$ (win in $\{l, h\}$).[36]

As outlined in the main text, conditional reasoning, as we understand it, requires two steps: (a) thinking in hypothetical situations and (b) conditioning on these hypothetical events when drawing appropriate conclusions on how to behave. In cursed equilibrium, agents remain able to think hypothetically, but draw misguided conclusions from these situations. As seen above, this alone is insufficient to explain overbidding behavior in our game.

Following CL, one has to assume a more general problem of conditional reasoning to explain behavior. In particular, subjects may not be able to think in hypothetical situations. More in line with our empirical results, a potential modeling approach could, hence, assume that subjects are not even able to distinguish between the two different hypothetical opponent types. Implicitly averaging bids for these types would then lead player i to believe that player j's bid is $a_j = x_i + b_j$. If we assume that player i processes the two possible item values in the same fashion and expects it to be x_i, the best response to $b_j = -8$ is to overbid j with $b_i = -7.99$. These overbidding incentives only vanish when both players bid $b = 0$.

A.4.2 Level-k Model

The level-k prediction for players with positive level-k that hold a uniform random level-0 belief is $b^k = -8$. The intuition is the following: Against a uniform random level-0 player, bidding $b_i = -8$ implies winning only in state l with a probability of 3/8 and leads to an expected payoff of $Eu_i = \frac{1}{2} \cdot \frac{3}{8} \cdot 5$. Deviating to higher bids, however, leads to a reduction in the winning payoff that is not compensated by the increase of the winning probability. Since best response functions do not differ between the auction and the transformed game, there is no difference in

[36] We choose to describe the "win in $\{l, h\}$" deviation to be $b_i = -1.99$ since the response $b_i = -2$ requires an understanding of the type-dependent tie-breaker. Moreover, the best response against the computer is the same with and without cursedness by a similar logic as outlined above.

Table A.2: Estimated level-k distribution.

Level-k	b^k	AH		TH		AC		TC	
		N	l^k	N	l^k	N	l^k	N	l^k
0	$(-3, 8]$	36	0.72	16	0.35	21	0.48	9	0.21
1	$(-7, -3]$	12	0.24	22	0.48	15	0.34	23	0.55
≥ 2	$[-8, -7]$	2	0.04	8	0.17	8	0.18	10	0.24
Total		**50**		**46**		**44**		**42**	

Notes: $\star C$ bids are adjusted (see footnote 24).

the equilibrium across games.[37] This shows that in our auction game, the type-dependence of the action space limits the interpretation of the level-k model and in particular level-1 players as reflecting informational naïveté. Otherwise, type-independent random level-0 play leads to level-1 play that could be interpreted as informationally naïve since it cannot extract information about signals (Crawford et al., 2013, p. 28). In our case, by the definition of a best response, a level-1 player engages in conditional reasoning since the type determines the limits of the level-0 bid distribution.[38]

A model with a level-0 belief of truthful play, $b^0 = 0$, suffers from the same interpretative limitation. We can use it, however, as an exercise to look at the types emerging on the basis of such non-strategic and naïve behavior. Higher level players only differ in their beliefs. They all engage in conditional reasoning and, hence, do not suffer from inferential naïveté.

In particular, such a model predicts average bids $b^0 = 0$, $b^1 = -5.99$, and $b^k = -8$, if $k \geq 2$, for both the auction and the transformed game. If we take into account noisy behavior in the simplest way and draw the line between types in the middle of their predicted bids, we get to predicted intervals as shown in table A.2. By treatment, the table further shows the number and fraction l^k of subjects falling into these categories for the games played against human opponents in part I.

In the presence of both conditioning and belief formation (AH), the estimated fraction of level-0 players is very high, unlike many level-k distributions previously estimated. Removing the need to condition and to form beliefs step by step leads to a normalization of the level-k distribution to a point where is has a standard hump-shape and an average level of at least 1.02 (TC).

[37]Against computerized opponents, since beliefs are fixed and level-k maintains the best response assumption, no overbidding is predicted.

[38]We abstract from any influence the differences between the games could have on the level-0 belief.

B Online Appendix

B.1 Learning

In this section, we first provide evidence that our central results regarding conditioning and belief formation remain robust when considering single periods and not the average of the three periods per game, as done in the main text. Afterwards, we additionally analyze the data from part II of the $\mathcal{AH}$ and the $\mathcal{TH}$ treatment, as the main text only analyzes data from part I of our treatments.

B.1.1 Single Period Play

In general, using the mean values for the three periods of each game leads to less noisy data than using single values. Additionally, the fact that subjects learn over time in some games but not in others should be interpreted as an additional result and not as weakness of our design. Nonetheless, we can explicitly incorporate this learning in our comparisons to analyze whether our results still hold under very unfavorable conditions when we disregard an important feature of the transformed games. As already outlined in the main text, subjects only improve their behavior in TH and TC (when these games are played first in $\mathcal{TH}$ and $\mathcal{TC}$).

Regarding our results that refer to the conditioning problem, we want to analyze whether we even observe a difference in $\star H$ and $\star C$ when we control for learning in the later games. When we compare bidding behavior and payoffs in $\star H$ and this time base this comparison only on the first period, subjects still bid significantly less (and earn significantly more) in TH (Wilcoxon rank sum, bids - $p = 0.018$, payoffs - $p = 0.050$). Additionally, plausible behavior is more likely in TH (Fisher's exact test, $p = 0.011$) than in AH. When comparing behavior in $\star C$ and considering only the first period, results still have the expected direction but are not generally significant (Wilcoxon rank sum, bids - $p = 0.146$, payoffs - $p = 0.388$; Fisher's exact test, $p = 0.057$).

Regarding our results that refer to the belief formation problem, we want to analyze whether subjects still improve their behavior in C compared to H even if we incorporate that subjects learn in the three rounds of the TH. When we compare TH and $TC_{\mathcal{TH}}$ and focus on third periods (to incorporate learning), the differences between the two settings naturally diminish and bids and payoffs are not significantly different any more (Wilcoxon rank sum, bids - $p = 0.143$, payoffs - $p = 0.871$). Importantly, we have different equilibria in both settings which biases against observing a difference in bids or payoffs. Hence, the more reliable measure is to consider whether the percentage of subjects playing plausible in both both settings change. Indeed, more subjects play plausible in $TC_{\mathcal{TH}}$ setting compared TH and this difference remains highly significant (McNemar's Test, $p = 0.001$). We obtain a similar result when we do the same analysis not within but between-subject (TH vs. TC), and again consider only the third period (Wilcoxon rank sum, bids - $p = 0.621$, payoffs - $p = 0.442$; Fisher's exact test, $p = 0.000$). Hence, as expected, results become slightly weaker when incorporating that subjects learn in the transformed games, but even then the overall pattern of the results remains intact.

Finally, we observe that learning in TH (when played first in $\mathcal{TH}$) leads to a similar effect on subjects bids than playing this game after the computerized version, $TH_{\mathcal{TC}}$ (TH -third period bid: -4.68 vs. $TH_{\mathcal{TC}}$ - mean bid: -4.64). A possible explanation for this effect is that in TH subjects might use their first period bid as a first belief for the consecutive periods in similar fashion as the play against the computer provides a first belief.

B.1.2 Part II Analysis

In the main text, our analysis focused on part I of the four treatments. In this section, we will additionally analyze part II of $\mathcal{AH}$ and $\mathcal{TH}$. If problems with conditional reasoning are at the origin of the WC, we should observe a different learning pattern from part I to part II between the two treatments. If conditional reasoning is an obstacle for understanding the A games (both in H and C), playing these game before the T games should not per se improve behavior in T. Subjects should not gain a better understanding of T via A simply because participants do not understand the A games because of the problems with conditional reasoning. Additionally, those subjects who manage to avoid the WC in A would most likely already play rationally in T if this game is played first. Playing T first, however, might very well facilitate playing A. By understanding the structure of T, a better understanding of the setting in which conditional reasoning on future events is necessary might arise. Hence, different patterns of learning behavior between the two treatments should be observed:

> ***Hypothesis 4:*** *In $\mathcal{AH}$, no learning effect is observed in part II. Playing the T games after playing the A games leads to similar results as first playing T. In $\mathcal{TH}$, however, a learning effect is observed: Playing the A games after the T games leads to more rational behavior than playing*

Table A.3: Summary statistics - $\mathcal{AH}$ & $\mathcal{TH}$ treatments (Part I & Part II)

		Part I		**Part II**	
Mean		$\mathcal{AH}$	$\mathcal{TH}$	$\mathcal{AH}$	$\mathcal{TH}$
(Std. dev.)		A	T	T	A
H	Bids	–1.80	–4.00	–3.66	–3.77
		(2.63)	(2.61)	(4.05)	(2.88)
	Payoffs	–0.56	0.55	0.05	0.29
		(1.55)	(1.37)	(2.29)	(1.90)
C	Bids	–3.37	–5.00	–3.04	–4.48
		(3.30)	(2.53)	(3.74)	(2.66)
	Payoffs	0.17	0.81	–0.16	0.68
		(1.53)	(1.56)	(2.09)	(1.53)

the A games first.[39]

We focus on $\mathcal{AH}$ and $\mathcal{TH}$ because both treatments potentially provide a better comparison for the predicted learning effect than $\mathcal{AC}$ and $\mathcal{TC}$. In the latter treatments, subjects also first play C in the second part which in principle could have an influence on H at the very end of each treatment.[40]

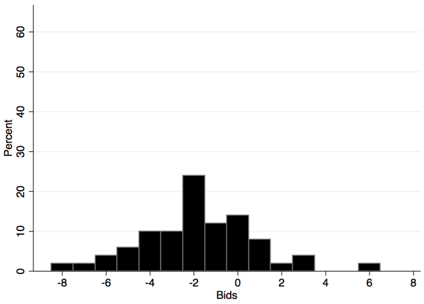
Table A.3 provides the mean values for subjects' bids and payoffs for part II of both treatments. Figure A.5 additionally shows histograms of subjects' bids in $\mathcal{AH}$ and $\mathcal{TH}$ for both parts.

When the auction game (against humans) is played after both T games, $AH_{\mathcal{TH}}$, only 28% of those subjects who win the auction face losses compared to 61% in AH. In line with this observation, bids in $AH_{\mathcal{TH}}$ are lower than in AH, whereas payoffs are higher (Mean values - bids: -3.77 vs. -1.80; payoffs $+0.29$ vs. -0.56).[41] Hence, there is clear evidence that playing the T games in $\mathcal{TH}$ before the A games helps subjects to avoid the WC in $AH_{\mathcal{TH}}$. Because of learning, we also do not observe the treatment effect between the two games within-subject in the $\mathcal{TH}$

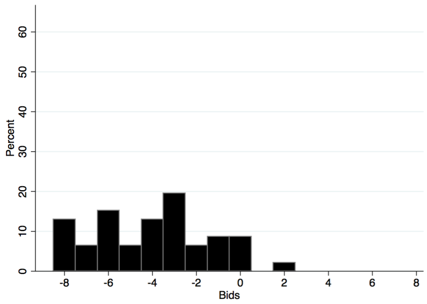
[39] Our design can, however, not distinguish whether such a learning effect is driven by the fact that subjects really understand the conditional reasoning because they played T first, or whether alternatively, subjects only understand that bidding low is a good strategy in T which they then also apply to A. It is, however, noteworthy, that subjects at least do not receive any feedback about the results and whether bidding low is a good strategy before the end of the experiment.

[40] In general, results for $\mathcal{AC}$ and $\mathcal{TC}$ are comparable to those in $\mathcal{AH}$ and $\mathcal{TH}$ to the extent, that playing A first does not help playing T, whereas playing T first helps playing A afterwards. This effect is significant in H, whereas in C the effect has the right sign but is insignificant. Hence, results in $\mathcal{AC}$ and $\mathcal{TC}$ are in general in line with our learning hypothesis. It might however, not be so clear, to what extent playing C first still influences these results.

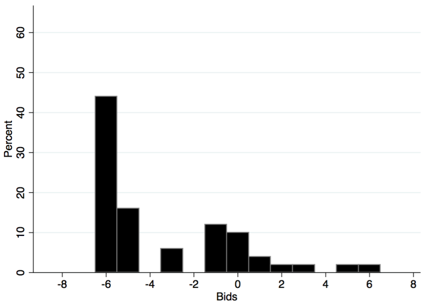
[41] Wilcoxon rank sum test - bids: $p = 0.000$; payoffs: $p = 0.002$. Fisher's exact test based on plausible play - p-value $= 0.025$.



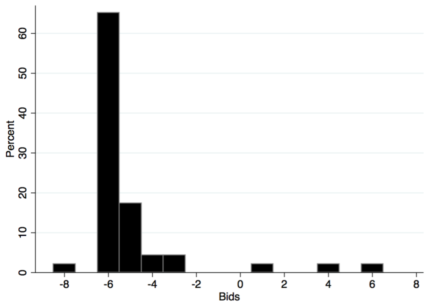
(a) AH, $N = 50$.



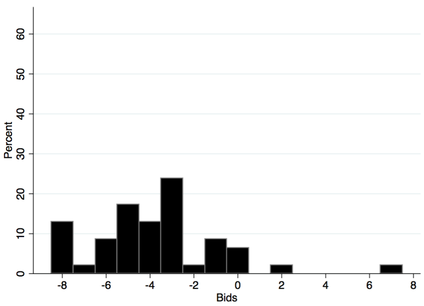
(b) TH, $N = 46$.



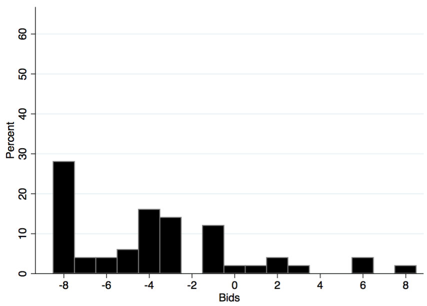
(c) $AC_{\mathcal{AH}}$, $N = 50$.



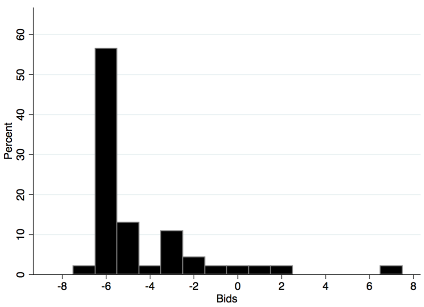
(d) $TC_{\mathcal{TH}}$, $N = 46$.



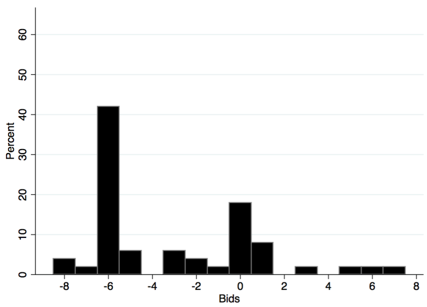
(e) $AH_{\mathcal{TH}}$, $N = 46$.



(f) $TH_{\mathcal{AH}}$, $N = 50$.



(g) $AC_{\mathcal{TH}}$, $N = 46$.



(h) $TC_{\mathcal{AH}}$, $N = 50$.

Figure A.5: Histograms of bids in $\mathcal{AH}$ and $\mathcal{AH}$.

treatment: Bids and payoffs are roughly the same between TH and $AH_{\mathcal{TH}}$ (Mean values - bids: -4.00 vs. -3.79; payoffs: 0.55 vs. 0.29).[42]

Do we also observe this learning effect for C? When the auction game is played after both T games, $AC_{\mathcal{TH}}$, only 22% of those subjects who win the game face losses compared to 45% in $AC_{\mathcal{AH}}$. In line with this observation, bids in $AC_{\mathcal{TH}}$ are lower than in $AC_{\mathcal{AH}}$, whereas payoffs are higher (Mean values - bids: -4.48 vs. -3.37; payoffs $+0.68$ vs. $+0.17$), although statistical analysis provides only partial support these findings.[43] Additionally, unlike in the case of H, the learning effect seems not to be strong enough to totally prevent a within-subject treatment effect.[44] Hence, there is some evidence for a learning effect in C of the $\mathcal{TH}$ treatment, but this learning effect seems to be weaker than in the H setting.

For the $\mathcal{AH}$ treatment, we hypothesized above that subjects do not benefit from playing A before T. For $TH_{\mathcal{AH}}$, 47% of those subjects who win the game face losses compared to 32% in TH. Additionally, bids in $TH_{\mathcal{AH}}$ are even slightly higher than in TH, whereas payoffs are lower (mean values - bids: -3.66 vs. -4.00; payoffs $+0.05$ vs. $+0.55$). Differences, however, are small and not statistical significant.[45] Because subjects do not learn in the $\mathcal{AH}$ treatment, we also observe the treatment effect between the two games within-subject in this treatment: Bids are higher in AH compared to $TH_{\mathcal{AH}}$, whereas payoffs are lower (mean values - bids: -1.80 vs. -3.66; payoffs: -0.56 vs. $+0.05$)[46]

How does the behavior in C evolve in the $\mathcal{AH}$ treatment? For $TC_{\mathcal{AH}}$, 43% of those subjects who win the game face losses compared to only 13% in $TC_{\mathcal{TH}}$ In line with this observation, bids in the $TC_{\mathcal{AH}}$ are higher than in $TC_{\mathcal{TH}}$, whereas payoffs are lower (Mean values - bids: -3.04 vs. -5.00; payoffs -0.16 vs. $+0.81$)[47] Hence, in the setting with computer opponents, we do not observe a learning effect, subjects in the $\mathcal{AH}$ treatment perform even slightly worse than in the $\mathcal{TH}$ treatment. For this reason, we also do not observe the treatment effect between

[42]Wilcoxon signed rank test - bids: $p = 0.814$; payoffs: $p = 0.833$. Additionally, a McNemar's test ($p = 0.6072$) based on plausible play reveals no significant difference.

[43]Wilcoxon rank sum test - bids: $p = 0.076$; payoffs: $p = 0.054$. But: Fisher's exact test based on plausible play: $p = 0.301$.

[44]Again, the statistical analysis is fairly inconclusive. A Wilcoxon signed rank test just reveals no significant difference (bids: $p = 0.101$; payoffs: $p = 0.371$) between $TC_{\mathcal{TH}}$ and $AC_{\mathcal{TH}}$, but a McNemar's test based on plausible play reveals such a difference with marginal significance (p-value $= 0.065$).

[45]Wilcoxon rank sum test: Bids - $p = 0.848$; payoffs - $p = 0.293$. Additionally, a Fisher's exact test based on plausible play supports this finding ($p = 0.834$).

[46]Wilcoxon signed rank tests: bids - $p = 0.000$; payoffs - $p = 0.003$. This result is also supported by a McNemar's test ($p = 0.002$) based on plausible behavior.

[47]Wilcoxon rank sum test: bids - $p = 0.033$; payoffs - $p = 0.007$. Fisher's exact test based on plausible play - $p = 0.001$.

the two games within-subject in the $\mathcal{AH}$ treatment: Bids and payoffs are fairly similar in $AC_{\mathcal{AH}}$ compared to $TC_{\mathcal{AH}}$ (mean values - bids: -3.37 vs. -3.04; payoffs: $+0.17$ vs. -0.16).[48]

> ***Result 4:*** In the H setting, we observe a learning effect as hypothesized: Playing the T games first facilitates playing the A games, whereas the reverse is not true. In C, a similar but weaker learning effect is observed in the $\mathcal{TH}$ treatment. Overall, however, rationality levels in the last game of both treatments are lower than expected. Exhaustion or increased confusion might be responsible for this result.

[48]Wilcoxon signed rank test: bids - $p = 0.980$; payoffs - $p = 0.205$. McNemar's based on plausible play - $p = 0.549$.

B.2 Figures: Individual Data

For completeness, figures A.6, A.7, A.8, and A.9 provide individual bids for all 12 periods of the experiment for all subjects of the four treatments. These figures support the evidence presented so far that subjects only improve their behavior in the transformed game when this game is played in part I of the experiment.

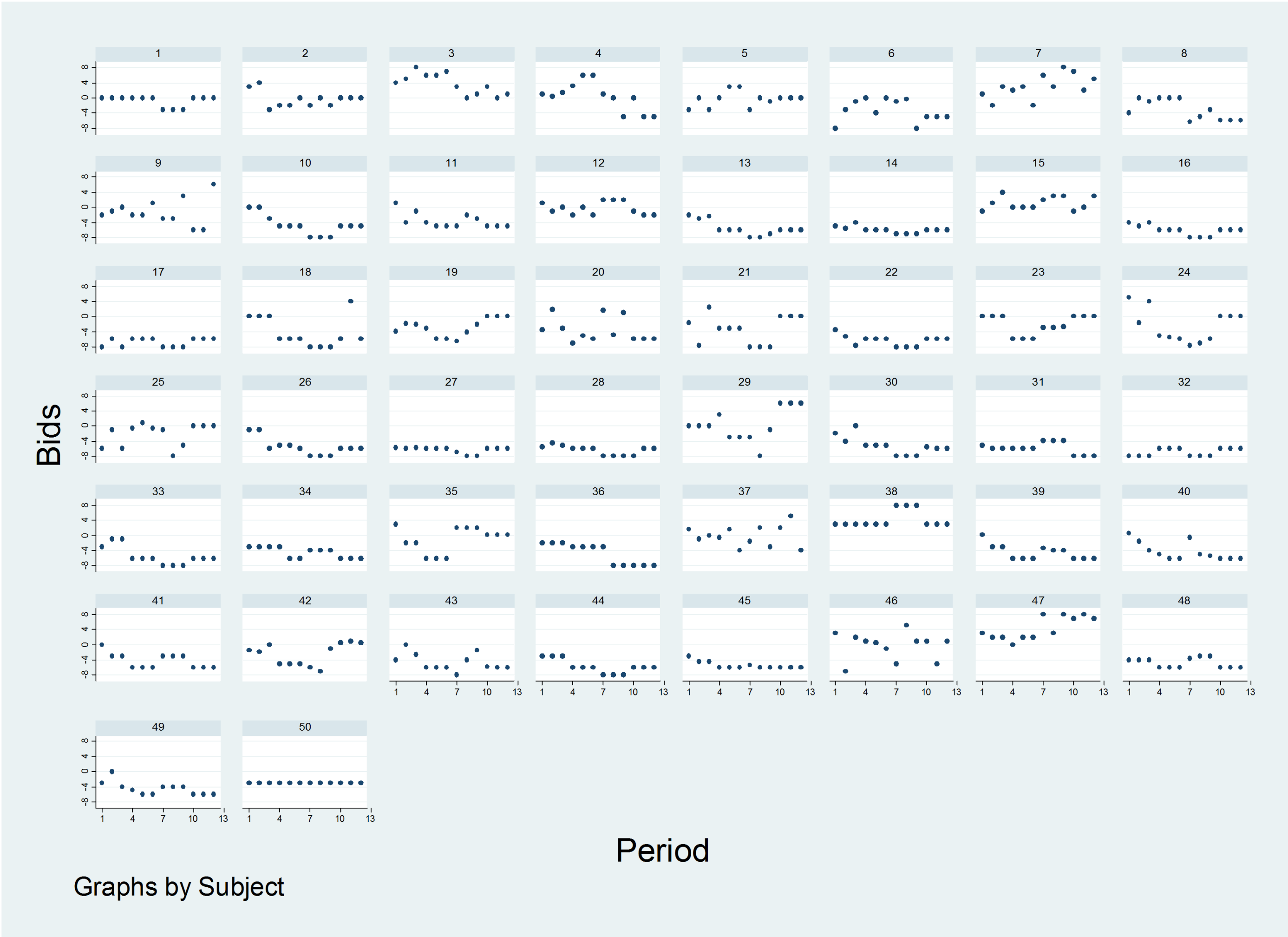


Figure A.6: Each subjects' behavior in the $\mathcal{AH}$ treatment (3 periods per game)

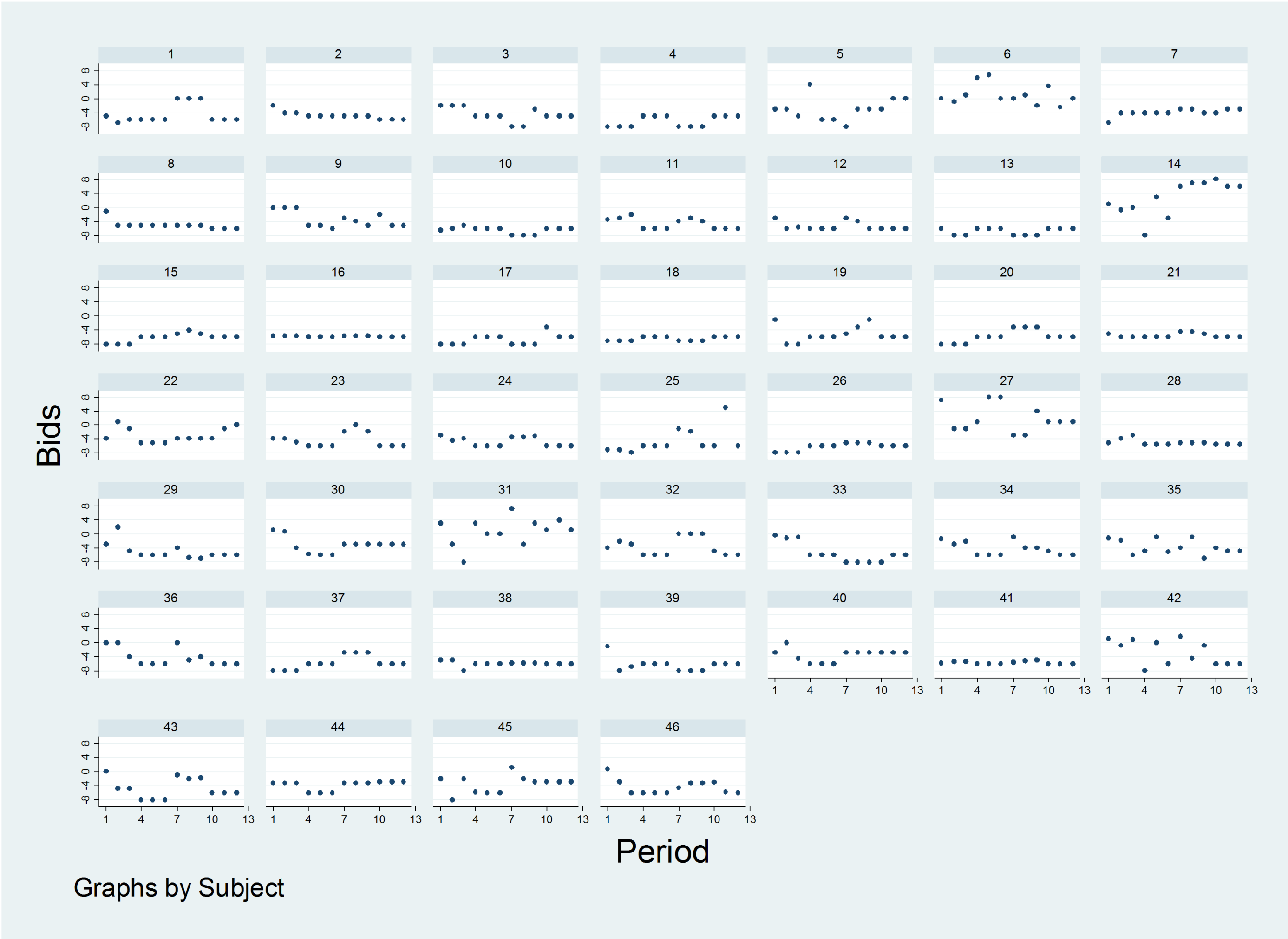


Figure A.7: Each subjects' behavior in the $\mathcal{TH}$ treatment (3 periods per game)

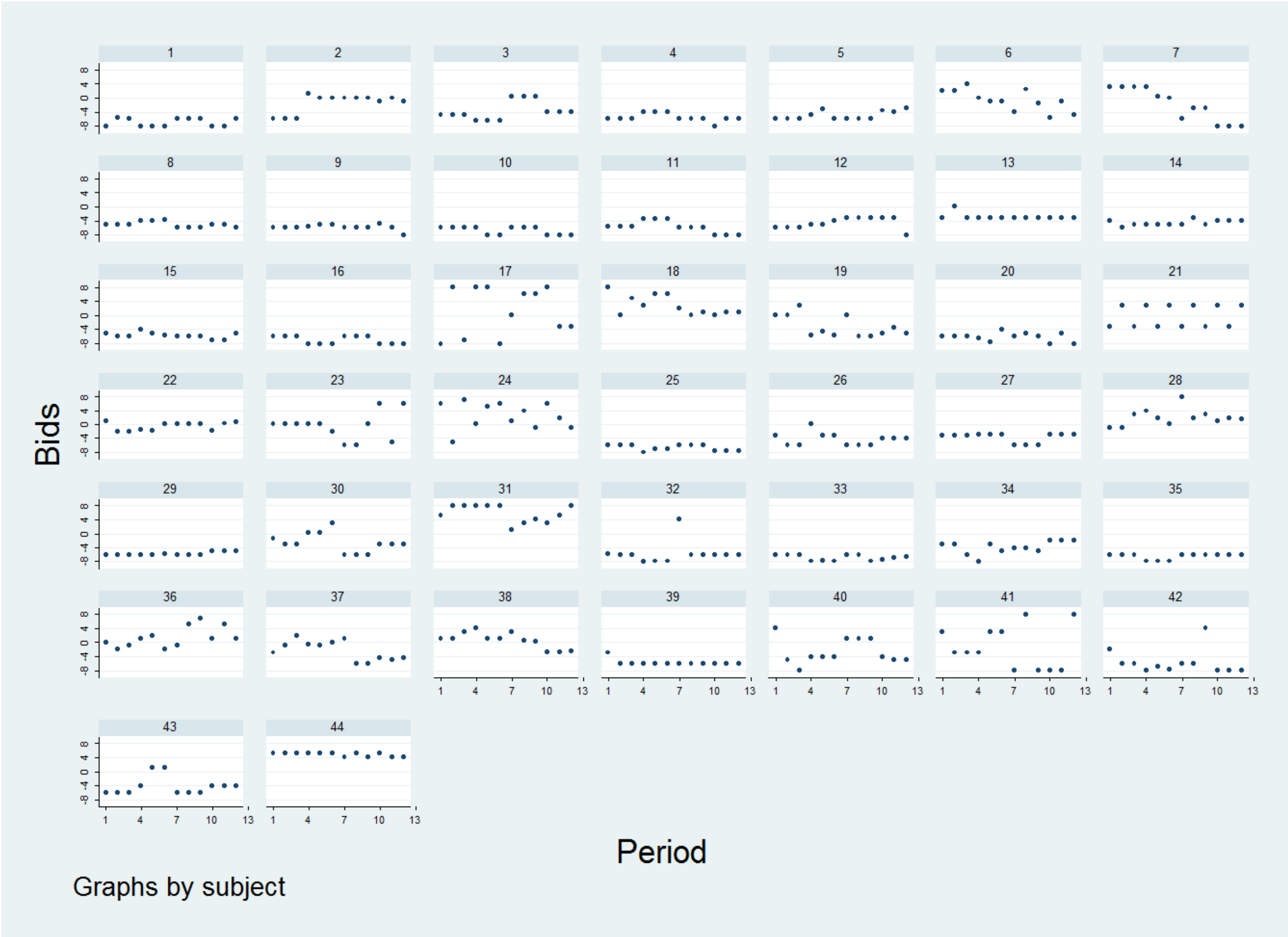


Figure A.8: Each subjects' behavior in the $\mathcal{AC}$ treatment (3 periods per game)

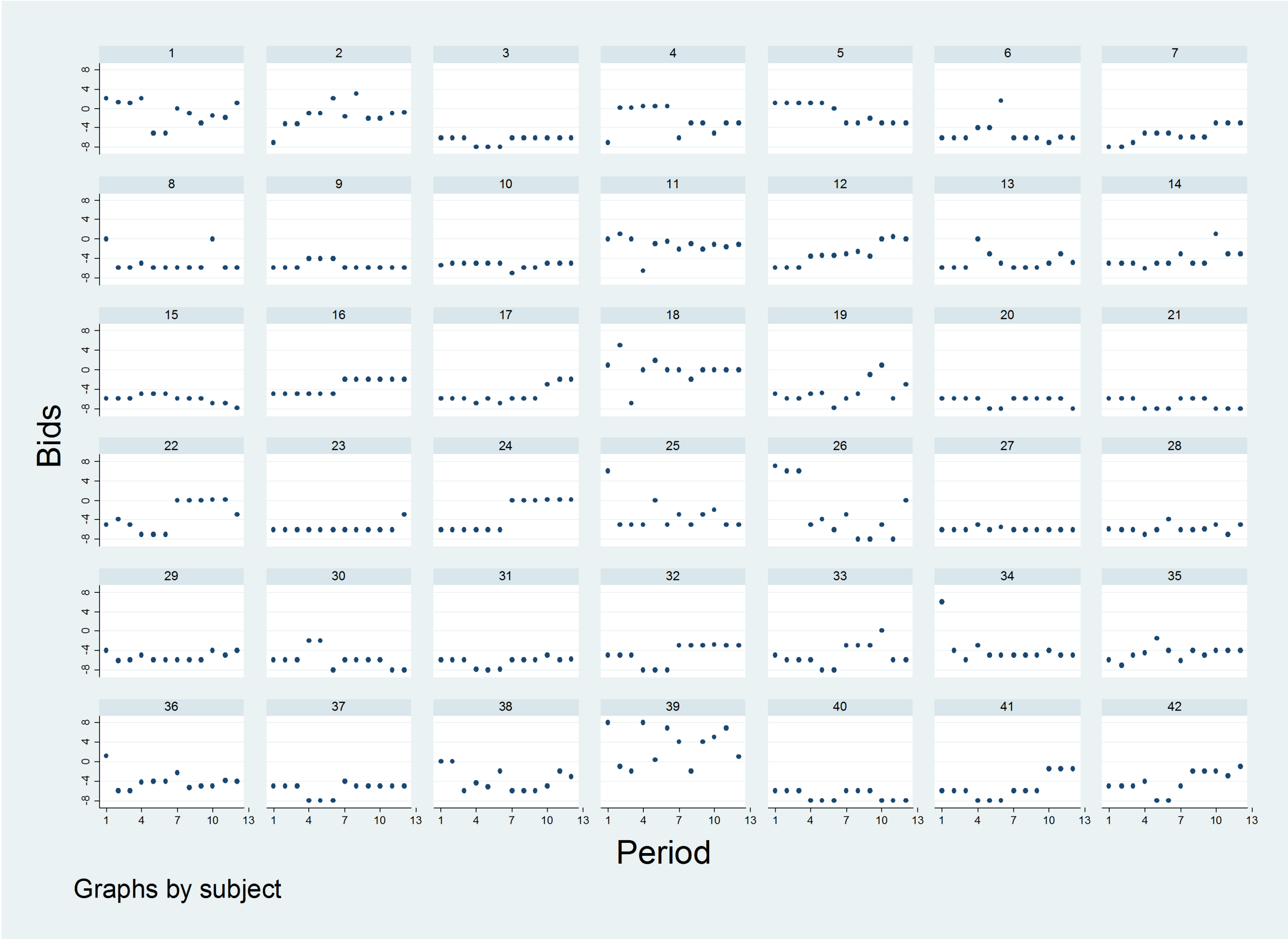


Figure A.9: Each subjects' behavior in the $\mathcal{TC}$ treatment (3 periods per game)

B.3 Instructions: $\mathcal{AH}$ treatment

Welcome to the experiment!

Introduction

I welcome you to today's experiment. The experiment is funded by the University of Mannheim. Please follow the instructions carefully.

For participating, you first of all receive a participation fee of 4€. Additionally, you may earn a considerable amount of money. Your decisions and the decisions of other participants determine this additional amount. You will be instructed in detail how your earnings depend on your decisions and on the decisions of other participants. All that you earn is yours to keep, and will be paid to you in private, in cash, after today's session.

It is important to us that you remain silent and do not look at other people's screens. If you have any questions or need assistance of any kind, please raise your hand, and an experimenter will come to you. If you talk, shout out loud, etc., you will be asked to leave.

The experiment consists of three parts. For all three parts, you will receive separate instructions. You will first make your decisions for all three parts and only afterwards **at the very end** of the experiment get to know which payments resulted from your decisions. The currency used in all three parts of the experiment is called Taler. Naturally, however, you will be paid in Euro at the end of the experiment. **Two Taler will then convert to one Euro.**

If you have any questions at this point, please raise your hand.

Part I

The first part of the experiment consists of 2×3 trading periods (thus trading periods 1-3 and trading periods 4-6). These instructions describe the decision problem as it is present in trading periods 1-3. This decision problem will be slightly modified in the trading periods 4-6. You will be informed about the details of this modification at the end of trading periods 1-3.

In this part of the experiment, you will act as a buyer of a fictitious commodity. In each trading period, you will have the opportunity to submit a bid for one unit of the commodity. Importantly, not only you will have this opportunity to make a bid for the commodity. In each trading period, you will be matched with another participant of this experiment. This participant will also have the opportunity to make a bid for the commodity. Importantly, you will always bid against another randomly determined participant in each trading period.

Your task is to submit bids for the commodity in competition with the other participant. The precise value of the commodity at the time you make your bids will be unknown to you. Instead, you and the other participant will receive an information signal as to the value of the item which you should find useful in determining your bid. Which kind of information you will receive, will be described below.

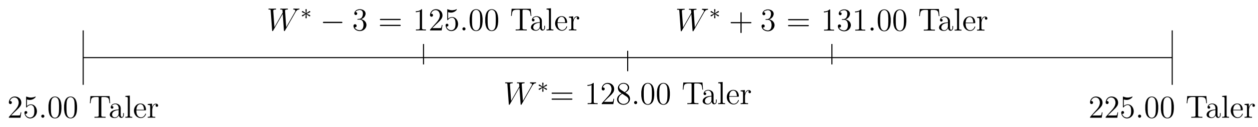
The value of the auctioned commodity (W^*) will always be an integer and will be assigned randomly. This value can never be below 25 Taler and never be above 225 Taler.[49] Additionally, the commodity's value W^* is randomly and independently determined from trading period to trading period. As such a high W^* in one period tells you nothing about the likely value in the next period

Private Information Signals: Although you do not know the precise value of the commodity, you and the participant who is matched with you will receive an information signal that will narrow down the range of possible values of the commodity. This information signal is either W^* – 3 or W^* + 3, where both values are equally likely. In addition, it holds that when you receive the information signal W^* – 3, the person who is matched to you will receive the information signal W^* + 3. If in contrast, you receive the information signal W^* + 3, the other person gets the information signal W^* – 3.

For example, suppose that the value of the auctioned item (which is initially unknown to you) is 128.00 Taler. Then you will either receive a) the information signal $W^* - 3 = 125.00$ Taler or b) the information signal $W^* + 3 = 131.00$. In both cases, the other person will receive the opposite information signal, in case of a) the information signal $W^* + 3 = 131.00$ and in case of b) the information

[49]The instructions do not specify explicitly that the item's value is *uniformly* distributed. This is, however, done implicitly by stating below that the item's value is either three points above or below players' signals with *equal* probability. We followed this implementation to minimize the difference between the auction and the transformed game. The rules of the transformed game only state the two probabilities with which the lower or the higher item value realize but do not need to explain what a uniform distribution – a potentially problematic concept – is. We inform subjects about the uniform distribution after the example and do not discuss the unequal probabilities at the boundaries. Since no participant ever asked a question about this particular part of the instructions, participants must have inferred that probabilities naturally differ at the boundaries from the signal generation process shown in the example.

signal $W^* - 3 = 125.00$ Taler. The line diagram below shows what's going on in this example.



It also holds that the commodity's value W^* is equal to the signal – 3 or the signal + 3 with equal probability. The computer calculates this for you and notes it.

Your signal values are strictly private information and are not to be revealed to the other person. In addition, you will only be informed about the commodity's value W^* and the other participant's bid at the end of the whole experiment (when also the second and the third part of the experiment are completed).

It is important to note that no participant is allowed to bid less than the signal – 8 and more than the signal + 8 for the commodity. Every bid between these values (including these values) is possible. Bids have at least to be rounded **to one cent**. Moreover, it holds that the participant who submits the higher bid gets the commodity and makes a profit equal to the differences between the value of the commodity and the the amount he or she bids. That is,

- Profit = W^* (128.00 Taler) – higher bid

for the higher bidding person. If this difference is negative, the winning person looses money. If you do not make the higher bid on the item, you will neither make a profit nor a loss. You will earn zero profits. If you and the other participant submit the same bid, the person who received the lower signal will get the commodity and he or she will be paid according to his or her bid.

At the beginning of part I, each individual participant will be given a starting capital credit balance of 8 Taler. Any profit earned by you in the experiment will be added to this sum. Any losses incurred will be subtracted from this sum. At the end of this part of the experiment, all gains and losses will be add up and the net balance of these transactions will be added to your captital credit balance. You are permitted to bid in excess of your capital credit balance. Even in case of a negative captial credit balance, you are still permitted to submit bids. Should your net balance at the end of this part of the experiment be zero (or less), you will not get any payoff from this part of the experiment. But even in case you make losses in this part of the experiment, you will keep your initial show-up fee of 4€.

Summary:

1. Two participants have the opportunity to submit bids for a fictitious commodity. The exact value of the commodity W^* is unknown to you. This value will, however, always be between 25 Taler and 225 Taler. Moreover, you receive a private information signal concerning the commodity's value. This signal is either $W^* - 3$ or $W^* + 3$. The other participant will receive the other signal. No one is allowed to bid less than the signal – 8 or more than the signal + 8.

2. The higher-bidding participant gains the commodity and makes the following profit = commodity's value - higher bid.

3. Profits will be added to your initial capital starting balance. Losses will be subtracted from your initial capital starting balance. You can always submit higher bids than your capital starting balance.

4. This part of the experiment consists of two rounds with overall 6 trading periods. These instructions describe the decision problem as it occurs in the trading periods 1-3. There will be a modification of the decision problem for rounds 4-6, about which you will be informed soon.

If you have read everything, please click the "Ready" button, to start the experiment.

Modifciation of the decision problem

You have now entered all decisions for the trading periods 1-3. Now, trading periods 4-6 will follow for which the decision problem so far will be slightly modified. As up to now the task is to submit bids for a fictitious commodity. Importantly, the other participant who also has the opportunity to submit bids will be replaced by the computer. As the other participant in the trading periods 1-3, the computer will also receive a signal about the commodity's value that is opposite to your own signal. The computer then decides according to the following decision rule: ***The computer always exactly bids his information signal***. Suppose, for example, that the true value of the commodity is 128.00 Taler. If the computer receives the information signal 125.00 Taler (commodity's value – 3), the computer's bid is equal to 125.00 Taler. If the computer receives the information signal 131.00 Taler (commodity's value + 3), the computer's bid is equal to 131.00 Taler. Otherwise, everything else does not change.

If you have read everything, please click the "Ready" button, to continue with the experiment.

Part II

The second part of the experiment consists of 3 trading periods (trading periods 7-9). In this part of the experiment, you will again act as a buyer of a fictitious commodity. In each trading period, you will have the opportunity to submit a bid for one unit of the commodity. Importantly, not only you will have this opportunity to make a bid for the commodity. In each trading period, you will be matched with another participant of this experiment. This participant will also have the opportunity to make a bid for the commodity. Importantly, you will always bid against another randomly determined participant in each trading period.

Your task is to submit bids for the commodity in competition with the other participant. In general, the value of the auctioned commodity will always be an integer and will be randomly determined. This value can never be below 25 Taler and never be above 225 Taler. At the beginning of each period, you and the other participant will be informed about the commodity's value. Importantly, however, there is a slight uncertainty about the value of the commodity. This value can take two different specifications in every period. The commodity can either be worth W_l^* or W_2^*, where both values always differ by 6 Taler and W_l^* always indicates the lower value. Which of the two values really realizes depends on chance and your bid as well as the other participant's bid and will be explained to you in more detail below. Both your bid and the other participant's bid are not allowed to be lower than $W_l^* - 5$ or higher than $W_2^* + 5$. Every bid between these values (including these values) is possible. Bids have at least to be rounded **to one cent**.

To make the rules of the auction understandable, they will be explained in detail with the help of an example. Suppose that at the beginning of one period, you are informed that the commodity's value is either $W_l^* = 107.00$ Taler or $W_2^* = 113.00$ Taler. You and the other participant are not allowed to bid less than $W_l^* - 5 = 102.00$ or more than $W_2^* + 5 = 118.00$ Taler. Who gets the commodity depends on your bid and the other participant's bid. Three rules apply:

1. **Your bid is 6.00 Taler or more higher than the other participant's bid:**
   In this case, you will get the commodity for sure. With a 50 percent chance each the commodity's value then is either W_l^* (107.00 Taler) or W_2^* (113.00 Taler). Hence, your profit is:

   - Profit = W_1^* (107.00 Taler) – Your bid   or
   - Profit = W_2^* (113.00 Taler) – Your bid

   Both scenarios are equally likely and the computer will randomly choose which scenario occurs. If one of the differences is negative and this scenario occurs, you will make a loss. The other participant will be paid according to rule 2.

2. **Your bid is 6.00 Taler or more below the other participant's bid:**
   In this case, you will not get the commodity in any case and your profit is zero. The other participant will be paid according to rule 1.

3. **Your bid is less than 6.00 Taler above or less than 6.00 Taler below the other participant's bid:**
   In this case, either you or the other participant get the commodity with a 50 percent chance and the computer will make this decision. The commodity's value is in any case W_1^* (107.00 Taler). Hence, in case you get the commodity, your profit is:

   - Profit = W_1^* (107.00 Taler) – Your bid

   In this case, the other participant earns zero Taler. If on the contrary, you do not get the commodity, your profit is zero and the other participant's profit is:

   - Profit = W_1^* (107.00 Taler) – His/her bid

   In both cases, it holds for the person who gets the commodity that this person will make a loss if the difference is negative.

At the beginning of part II, each individual participant will be given a starting capital credit balance of 8 Taler. Any profit earned by you in the experiment will be added to this sum. Any losses incurred will be subtracted from this sum. At the end of this part of the experiment, all gains and losses will be add up and the net balance of these transactions will be added to your captital credit balance. You are permitted to bid in excess of your capital credit balance. Even in case of a negative captial credit balance, you are still permitted to submit bids. Should your net balance at the end of this part of the experiment be zero (or less), you will not get any payoff from this part of the experiment. But even in case you make losses in this part of the experiment, you will keep your initial show-up fee of 4€.

You will only be informed about the other participant's bid and which value of commodity actually has realized at the end of the whole experiment (when also the third part of the experiment is completed).

Summary:

1. Two participants have the opportunity to submit bids for a fictitious commodity. The value of commodity will always be between 25 Taler and 225 Taler. Because of uncertainty, the commodity's value can take two specifications W_1^* and W_2^*, where the difference between both values is always 6 Taler. No one is allowed to bid less than $W_1^* - 5$ and more than $W_2^* + 5$.

2. If one person bids at least 6.00 Taler more than the other person, this persons gets the commodity for sure and either makes the profit $= W_1^* -$ his/her bid or the profit $= W_2^* -$ his/her bid. If one person bids at least 6.00 Taler less than the the other person, this person does not get the commodity in any case and makes a profit of zero Taler. If the difference of the bids is less than 6.00 Taler, both participants get the commodity with a 50 percent chance and make the following profit $= W_1^* -$ his/her bid in this case.

3. Profits will be added to your initial capital starting balance. Losses will be subtracted from your initial capital starting balance. You can always submit higher bids than your capital starting balance.

4. This part of the experiment consists of 3 trading periods.

If you have read everything, please click the "Ready" button, to continue with the experiment.

Part III

The third part of the experiment consists of 3 trading periods (trading periods 10-12). These 3 trading periods are almost identical to the trading periods 7-9 of part II. In addition, your capital credit balance of the end of part II will be the starting capital credit balance of this part. Hence, the payoff you receive from part II and part III of the experiment will finally depend on the amount of the capital credit balance at the end of this part of the experiment. In part III of the experiment, the following modification of the decision problem of part II is implemented: As up to now the task is to submit bids for a fictitious commodity. Importantly, the other participant who also has the opportunity to submit bids will be replaced by the computer. As the other participant in the trading periods 7-9, the computer is informed about both possible values of the commodity. The computer then decides according to the following decision rule: ***The computer always exactly bids the mean value of both values of the commodity (hence*** $\frac{W_1^*+W_2^*}{2}$ ***or*** $W_1^* + 3 = W_2^* - 3$***).*** Suppose, for example, that the true value of the commodity is either $W_1^* = 107.00$ Taler or $W_2^* = 113.00$ Taler. The computer will then bid 110.00 Taler ($\frac{107+113}{2} = 107.00 + 3.00 = 113.00 - 3.00$). Otherwise, everything else does not change.

If you have read everything, please click the "Ready" button, to continue with the experiment.

B.4 Instructions: Frequently Asked Questions

Auction game

1. *When I make my decision about which bid to submit, what kind of specific information do I have? Do I know the true value of the commodity?*
   You do not know the commodity's value W^*. When making your decision, you only know your private information signal. You also do not know whether you received the "high" or the "low" signal. You only receive one number. With a 50 percent chance, you have received the high signal and with a 50 percent chance you have received the low signal. All this also holds correspondingly for the other participant.

2. *On what does it depend whether I get the commodity and how much do I earn should this situation arise?*

The person who submits the higher bid gets the commodity. The profit then is: W^* – higher bid. If both bids are exactly the same (meaning bids are also the same on the cent-level), the person with the lower signal gets the commodity.

3. *Which values am I allowed to bid?*
   You are allowed to under- and overbid your personal information signal by up to 8.00 Taler. In addition, it is important that you are not only allowed to bid integers. For example, you could also bid 30.45 Taler instead of 30 Taler.

Transformed game

1. *When I make my decision about which bid to submit, what kind of specific information do I have? Do I know the true value of the commodity?*
   When making your decision, you know about two possible specifications of the commodity's value: W_1^* and W_2^*. Which of these values actually realizes in the end depends on your decision, the other participant's decision and chance.

2. *On what does it depend whether I get the commodity and how much do I earn should this situation arise?*
   If you at least bid 6.00 Taler more than the other person, you will get the commodity for sure. Your profit will then be W_1^* – your bid or W_2^* – your bid, with a 50 percent chance each. Conversely it holds, that if you bid at least 6.00 Taler less than the other person, you will not get the commodity and your profit will be zero. If the difference of the bids is smaller than 6.00 Taler, either you or the other participant gets the commodity with a 50 percent chance and the computer will make this decision randomly. If the computer chooses you as the winner, your profit will be W_1^* – your bid.

3. *Which values am I allowed to bid?*
   You are allowed to underbid the lower value of the commodity W_1^* by up to 5.00 Taler and overbid the higher value of the commodity W_2^* by up to 5.00 Taler. In addition, it is important that you are not only allowed to bid integers. For example, you could also bid 30.45 Taler instead of 30 Taler.