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Learning and Knowledge Transfer in Cooperative Groups and Competitive Auctions

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Abstract

There is strong evidence that groups perform better than individuals do on intellective tasks with demonstrably correct solutions. Typically, these studies assume that group members share common goals. In this paper, we extend this line of research by replacing standard face-to-face group interactions with competitive auctions, allowing for conflicting individual incentives. In a series of studies involving the well-known Wason selection task, we demonstrate that competitive auctions induce equally impressive learning effects as standard group interactions, and we uncover specific and general knowledge transfers from these institutions to new reasoning problems. We identify payoff feedback and information pooling as the driving factors underlying these findings, and we explain them within the theoretical framework of collective induction.

Keywords: Collective induction; Reasoning errors; Knowledge transfer; Cooperative groups; Competitive auctions.

Collective Induction without Cooperation?

Learning and Knowledge Transfer in Cooperative Groups and Competitive Auctions

Many important decisions in a variety of domains are routinely made in group settings: legislatures decide which bills to pass into law; juries determine the guilt of defendants and the amount of damages awarded to plaintiffs; school boards make decisions about curricula; corporations and universities appoint committees to make hiring and promotion decisions; and family members gather to deliberate on important decisions, such as where to spend their holiday.

The confidence that individuals, in private and professional settings, have in group decision-making seems to be substantiated by empirical evidence. Research on group problem-solving involving intellective tasks (Laughlin, 1980), with demonstrably correct solutions, has shown that groups usually perform better than individuals (Hill, 1982). Previous research has also documented positive knowledge transfers from interactive groups to individual behavior, indicating that simple group settings provide valuable learning opportunities for subsequent tasks (Laughlin & Adamopoulos, 1980).

This line of research implicitly assumes that group members will cooperate to achieve a common desirable goal. In many real-world situations, however, conflicts of interest and competition may exist between group members. In this paper, we investigate whether shared motives and cooperation are, indeed, necessary to achieve the beneficial effects of groups. More specifically, we test whether the superiority of group performance, and the positive transfer of knowledge, can be obtained when group members are competing with each other. To this end, we conducted a series of studies involving the well-known Wason selection task, which is “the single most investigated problem in the psychology of reasoning” (Evans & Over, 1996, p.356).

A simple and straightforward way to study the impact of competition on group decision-making is to endow the group members (or a subset thereof) with competitive individual motives. This manipulation, however, has been shown to induce information distortion and selective information sharing among group members (Hollingshead, Wittenbaum, Jacobsohn, & Fraidin, 2005). Research in economics suggests an alternative approach without such detrimental effects. Competitive markets have been shown to effectively disseminate and aggregate information, despite conflicting individual motives.

Camerer (1987) discusses some of the key features that account for markets' success in this respect: (a) markets provide individual financial incentives for acquiring and holding profitable assets; (b) only a small number of "informed" or "rational" traders are needed to ensure that aggregate market variables, such as prices or volumes, reflect their private information and knowledge; (c) markets provide periodic feedback about trading earnings; (d) less informed traders may learn implicitly and/or explicitly from the actions of the more informed traders; (e) aggregate market variables are disproportionally affected, and driven to a large degree, by a minority of active, intelligent, and informed traders; and (f) less informed or less rational traders may be driven from the market by bankruptcy.

In this paper, we use markets as an alternative to standard groups, in order to study the impact of competition on learning and knowledge transfer. Participants trade the solutions to the Wason selection task over repeated trials in competitive auctions. Solution cards are in limited supply, and those who acquire them receive considerable financial rewards. Competition for the solution cards, and the monetary rewards associated with them, induce conflicting individual incentives among auction participants. Unlike standard (cooperative) group settings, in which subjects' payoffs are not affected by the number of fellow group members who know the solution to a task, competitive auctions reduce individual payoffs as a function of the number of correct solutions: the more people know the solution to a problem, the lower the expected individual payoff.

This setup allows to us to study the effects of competition and conflicts of interest. We compare reasoning at the individual and aggregate level, contrast interacting groups with group auctions, and study knowledge transfers by introducing new, post-interaction, reasoning tasks. The paper proceeds with brief overviews of the relevant literature on group decision-making and competitive auctions.

Groups and auctions as effective information pooling institutions

A long stream of research documents the powerful effects of groups. Groups have been shown to outperform individuals in a variety of domains (Davis & Hinsz, 1982) and have been identified as effective institutions for disseminating and aggregating information, allowing for positive knowledge transfers from interactive settings to individuals. A useful distinction in the analysis of group processes is between judgmental and intellective tasks. Judgmental tasks are characterized by uncertainty and inconclusive or delayed feedback, whereas intellective tasks have a single optimal or correct outcome that can be demonstrated unambiguously. This taxonomy of decisions allows the derivation of precise predictions regarding the underlying group processes.

Probably the most successful theoretical analysis of small group decisions is the social decision scheme theory (Davis, 1973), which describes group interaction as a combinatorial process, allowing for the aggregation of individual preferences to reach consensus on a singular group choice (Tindale, Kameda, & Hinsz, 2003). This theory predicts that the dominant decision scheme in judgmental tasks is the majority rule, leading the group to perform at the level of a typical or “median member” (Hastie & Kameda, 2005). In intellective tasks the dominant decision scheme is “truth wins,” implying that the optimal, or correct, outcome can be explained to all group members, and the group members will eventually endorse it. In this case, groups are expected to perform at the level of the best of an equivalent number of individuals.

The predictions of the social decision scheme theory have been supported in a large number of studies. Examples of judgmental tasks are the selection of political candidates (Stasser & Titus, 1985), mock jury deliberation (Kameda, 1991), and detection tasks (Sorkin, West, & Robinson, 1998). Examples of intellective tasks are rule induction problems (Laughlin, Bonner, & Altermatt, 1998), and Mastermind problems (Bonner, Baumann & Dalal, 2002). In some intellective tasks, groups performed even better than the best (of an equivalent number) of individuals (see Laughlin, Bonner, & Miner, 2002; Laughlin, Zander, Knievel, & Tan, 2003; and Lauglin, Hatch, Silver, & Boh, 2006, for letters-to-numbers problems).[1]

Groups also have been shown to be effective in transferring knowledge from interactive settings to individuals facing intellective tasks. Laughlin and Adamopoulos (1980), for instance, observed specific group-to-individual transfers for verbal analogy tasks. Stasson, Kameda, Parks, Zimmerman, and Davis (1991) documented general group-to-individual transfers for geometry, algebra, and probability problems, by introducing new individual transfer problems (of the same type). Similar results were observed by Olivera and Straus (2004) for brainteasers and general knowledge problems.

While research in social psychology has studied interactive cooperative groups, economics has focused primarily on markets and auctions as disseminators and aggregators of information. Plott and Sunder (1982), for instance, studied a market in which traders could obtain one of two possible dividends depending on the realization of a randomly determined

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[1] For positive synergy effects among group members in signaling games see Cooper and Kagel (2005).

"state of the world." Although only half the traders were informed about the realized state, market prices revealed the true state, demonstrating the dissemination of private information. Another study by Plott and Sunder (1988) illustrates how information aggregation can be achieved in competitive markets. In this experiment, dividends could take three different values contingent upon the state of the world (X, Y or Z). Traders obtained private incomplete information. For example, when state Z was realized, half the traders were informed that the current state of nature was not X, whereas the other half were told that it was not Y. The market was capable of aggregating the imperfect private information of the traders, revealing the correct state of nature, Z.

These findings demonstrate that aggregate market variables, such as trading prices and trading volume, can reflect a competitive equilibrium, implying that supply equals demand, even if no single trader has sufficient information to compute it. They also suggest that traders acting on private information and pursuing self-interest could be sufficient for the emergence of the equilibrium. These results inspired researchers to use markets as forecasting instruments. Successful applications include the predictions of election outcomes (Forsythe, Nelson, Neumann, & Wright, 1992), winners of sport events (Schmidt & Werwatz, 2002) and entertainment awards (Pennock, Lawrence, Giles, & Nielsen, 2001), as well as box office returns (Spann & Skiera, 2003), potential sales (Chen & Plott, 2002), and market shares for new products (Chan, Dahan, Kim, Lo, & Poggio, 2002).

While research in psychology has tried to identify the rules and mechanisms underlying group decisions, economists have studied primarily the necessary and sufficient conditions for attaining equilibrium (Kagel, 1995; Sunder, 1995) and designing specific trading mechanisms for certain allocation tasks (Milgrom, 2004). Examples include designing of the matching market for physicians in the United States (Roth & Peranson, 1999), spectrum auctions (Cramton, 1998), and the market for organs (Roth, Sönmez, & Ünver, 2004).

A comparison of groups and auctions

Laughlin and his colleagues (e.g. Laughlin, 1996, 1999; Laughlin & Holingshead 1996) have studied systematically the process of collective induction in group decision-making, and defined it as the cooperative search for descriptive, predictive and explanatory generalizations, rules and principles on the basis of empirical manifestations of the target rules and principles. Auctions, on the other hand, are defined as platforms that allow potential purchasers to bid competitively for goods and/or services, rather than simply paying the seller's asking price. Continuous auctions that allow instantaneous price adjustment as a function of supply and demand are defined as auction markets. Such markets trade standardized items anonymously and require a sufficient number of bidders to ensure competitive behavior (Pearce, 1999).

Despite the obvious difference between their cooperative and competitive aspects, groups and auctions share a number of important features. This becomes apparent upon examination of the theoretical framework of collective induction encapsulated in Laughlin's 12 postulates (Laughlin, 1999). Postulates 3 and 5, taken jointly, imply that groups can solve intellective tasks correctly even if only a small minority of participants (as small as a single person for mathematical problems) knows the correct solution. Postulate 9 states that collective induction is comparable in quality to the best solution proposed by (a similar number of) individuals. Finally, postulate 4 lists the four conditions required for demonstrability. The first two refer to the group and the decision environment: (a) the group should agree on a conceptual system (rules, terminology, etc.), and (b) there should be sufficient information available for the group to find a solution. The other two conditions refer to individual participants: (c) members who endorse incorrect solutions should be able to recognize the correct solution if it is presented to them, and (d) members who know the correct solution should have the ability, time, and motivation to demonstrate it to those who hold incorrect beliefs. Clearly, the motivation to cooperate with other members is a critical component of this process.

The corresponding features of competitive auctions relate to their ability to disseminate and aggregate information effectively. Analyses of aggregate market variables, such as prices, reflect the solution to a problem, even if only a small minority of traders solved it individually, implying that Postulates 3, 5, and 9 are satisfied. Markets also satisfy most conditions of Postulate 4: (a) auctions apply strict and commonly known rules (e.g., how and when to submit bids, how to determine auction winners), (b) the traders have the necessary information to identify the correct solution to a task, (c) auction participants who endorse incorrect solutions are able to recognize the correct solution when exposed to a variety of structured information (e.g., who bids, how much, on what), which is public knowledge. The key difference between interactive groups and auctions pertains to the last condition: (d) auction participants who know the correct solution (i.e., the value of the good) do not necessarily want to share their information with others. In fact, they have strong incentives not to divulge it to their competitors, but the public nature of the auction prevents them from withholding it indefinitely (although they could adopt various convoluted strategies designed to disguise it at least temporarily). The main goal of this study is to compare these two institutions.

The present studies

We study (a) whether groups and auctions perform better on reasoning problems than individuals do, (b) whether these institutions enable their members to successfully transfer knowledge to new reasoning tasks, and (c) we compare their relative level of success in disseminating and aggregating information. Finally, we introduce post-interaction reasoning tasks to investigate (d) the rate of general knowledge transfer from the interacting groups and auctions to new reasoning problems solved individually.

For this purpose, we use several versions of the Wason selection task and allow participants in some of our studies to acquire potential solutions to it in a combinatorial auction. Next, we will describe the Wason selection task, the auction mechanism, and provide a short example of a typical auction trial.

The Wason selection task

This task was originally designed to test whether individuals employ the normatively correct strategy, as prescribed by formal logic, in testing conditional rules of the form "if p, then q" (Wason, 1966). In the standard setup, participants are shown four cards, each with a letter (vowel or consonant) on one side and a number (even or odd) on the other side. The participants' task is to verify the conditional rule "if there is a vowel (p) on one side of the card, then there is an even number (q) on the other side," by identifying the minimal number of cards that must be turned over to decide whether the rule is true or false. Four cards are shown to the participants, who can only see one side of each card. The displayed cards are E (p), K (not-p), 2 (q), and 7 (not-q). The truth table of formal logic requires checking (a) the truthful implication of the rule by turning the card showing E (p), and (b) the potential falsification of the rule by turning the card showing 7 (not-q).

Typically, only about 10% of the participants solve this task correctly (Griggs & Cox, 1983). Most participants either select the p-card showing E, or the incorrect combination of the p- and q-card (E and 2). These findings have been replicated in numerous studies (Griggs & Cox, 1983), rendering the Wason selection task one of the most studied reasoning problems. From our perspective the task is a natural choice because (a) it has a well defined, unique, and demonstrable solution, and (b) its relative difficulty guarantees ample opportunities for learning in our groups and auctions.

The auction mechanism

Auctions have been used since antiquity for the sale of goods and services (Krishna, 2002), and many different auction formats are used for a variety of different purposes (e.g., allocating airport time slots, emissions and water rights). For the purpose of this short introduction, we restrict ourselves to double auctions and to combinatorial auctions.

The double auction: In a double auction, participants can engage in buying and selling at the same time. In the simplest case trading involves only two commodities, the good and money, and requires the exchange of one for the other. Consider the following simple market, which involves three traders (A, B, and C), each of whom is endowed with a colored coffee mug and some cash. Assume trader A has a red mug, trader B a yellow mug, and trader C a blue mug. Also, assume that A prefers blue, B prefers red, and C prefers yellow. Each trader can now engage in four activities: (a) submit a bid for the preferred mug (e.g., trader A might announce that she is willing to buy the blue mug for $3), (b) submit an ask to sell one’s mug (e.g., trader B might announce that he is willing to sell his mug for $3.50), (c) engage in both activities at the same time (e.g., trader C bids $2 for the yellow mug and indicates that she would sell her blue mug for $3), or (d) refrain from trading. Since trader A’s bid for the blue mug ($3) equals trader C’s ask ($3), the two can exchange the money for the mug. After information about this transaction becomes public, the traders might want to reconsider their bids and asks. Trading ends when no more voluntary trades occur.

A variant of the double auction was implemented in a recent paper by Budescu and Maciejovsky (2005), who studied the persistence of reasoning errors in the Wason selection task in this competitive institution. The auctions consisted of eight traders and were conducted by computer (allowing anonymous trading). Each participant was endowed with several exemplars of one of the four cards (p-card, not p-card, q-card, or not q-card) and some cash. Each set of correctly paired cards (p-card and not q-card), earned dividends at the end of every three-minute auction trial. Neither partial solutions nor incorrect card combinations earned financial rewards. Thus, if a trader figured out that the correct solution consisted of the cards p and not q, he/she would have to acquire these cards in the auction in order to receive financial rewards. These experiments showed that payoff feedback, which was provided in some experimental conditions after each auction trial, drove aggregate trading variables (e.g., trading prices and volume) toward the normative solution. However, mere exposure to the information flow created by traders (including some who knew the correct solution), by observing the bids and asks submitted by these traders did not affect the trading behavior (or earnings) of participants who did not know the correct solution, and also did not receive payoff feedback (see experiments 1 to 3 in Budescu and Maciejovsky, 2005).

We hypothesize that learning in markets can also be achieved under weaker conditions, without providing direct individual payoff feedback. We use an auction mechanism that is better suited for this purpose than the one used by Budescu and Maciejovsky (2005), which exposed traders to execution risk. Rational traders should be willing to pay up to the total dividend amount for both cards, but zero for either card alone. Since the double auction forces traders to acquire the two solution cards separately, traders risk failure by acquiring only one of the desired cards. In the present study, we use a combinatorial auction mechanism that eliminates this risk.

The combinatorial auction: These auctions allow participants to submit bids for each of the possible 15 card combinations, including individual cards (see Figure 1 for a screen-shot of the auction, and a complete listing of the card combinations). At the beginning of each auction trial, the participants are endowed with cash. During a trial, participants can submit their bids for any combination of their desired cards continuously (as long as they have enough cash). To increase the competitive nature of the auction, we restricted the number of cards being auctioned. After an auction trial ends, the winners of the auction are determined by a process that assures that the auctioneer's (experimenter's) revenue (i.e., the bids before dividends) is maximized subject to the constraint of card availability. This maximization problem (for a brief discussion, see Pekeç & Rothkopf, 2003) is solved by a computer algorithm (based on exhaustive enumeration of card partitions; see Sandholm, 2002).[2] After the winners are identified, the participants are informed whether they obtained their desired cards. A concrete example of the winner determination process will be presented in the next section.

In our experiments, the four subjects who participated in each combinatorial auction were randomly assigned the labels A, B, C or D. Multiple auctions were performed in any given experimental session, ensuring that participants did not know with whom they interacted. All auctions were computerized ensuring anonymity and eliminating direct communication. Each auction trial lasted for 60 seconds, and each session consisted of 30 trials. At the beginning of every trial, each participant was endowed with 500 Experimental Currency Units (ECU).[3] Then, the Wason task was described, and subjects were instructed to acquire cards they believed to be part of the correct solution (more details will be provided in our description of the actual experiments). Each winning bid that included a complete set of

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[2] In case of multiple bids with identical revenue, ties are broken according to the timing of bids, favoring early bids. If ties cannot be broken by timing, a random device is employed.

[3] One hundred ECU were equivalent to € 1.

correct cards, i.e., those cards that make up the solution (in addition to, possibly, other cards), was rewarded with dividends of 200 ECU.

The computer screen allowed participants to keep track of their mean bids and demands in the last four trials (including the current one) for each possible card combination (see Figure 1). Demand, defined as the quantity of bids, was displayed in parentheses next to the mean bids. Similar information on the trading behavior of fellow auction participants was also available. The computer also kept track of the remaining trading time and the current trial number.

The following short example illustrates a typical auction trial and its winner determination process. For the remainder of the paper, we will refer to the p-card as card I, the not p-card as card II, the q-card as card III, and the not q-card as card IV.

Some numerical examples of an auction trial

Figure 1 displays the trading screen, showing the information that might have been available to a hypothetical group of four participants on their fourth auction trial. It shows the bids for each subject (A, B, C, and D) on the previous three trials (labeled 1, 2, and 3 in the various tables associated with the traders), which we will use in the following to describe the bidding behavior and the winner determination procedure. For simplicity, we assume in all the examples that only one card of each type is auctioned off (note that in the actual auction there were four cards of each type available).[4] Further, assume that endowment leftovers (i.e., residual cash after bidding) cannot be converted to cash at the end of trading. This creates incentives for subjects to engage in bidding rather than simply saving endowments for final payoffs.

[4] This assumption renders some of the bids displayed in Figure 1 not entirely realistic, because some participants in this example submitted multiple bids for cards.

In the first example (trial 1) only the bids for participants A and B are displayed. Participant A submitted bids of 190 ECU for the bundle of cards I and III, and 155 ECU each for the bundle of cards I, II, III, and I, III, IV. Participant B submitted 70 ECU for card II, 69 ECU for card III, 1 ECU for card IV, 180 ECU for the bundle II and III, and 180 ECU for the bundle of cards I, II, III, and IV. The auctioneer's revenue will be maximized by allocating the bundle I and III to participant A and the cards II and IV to participant B. Since only one card of each type is available for allocation, the other bids will not be allocated. The auctioneer's revenue is 190 + 70 + 1 = 261 ECU, and since neither participant holds the correct cards (I and IV) they do not obtain dividends.

Consider now trial 2, displayed in Figure 1, that involves only participants C and D. Participant C submitted one bid of 80 ECU for each of the four cards separately and one bid of 180 ECU for the bundle of cards I, II, III, and IV. Participant D submitted one bid of 190 ECU for the bundle I and IV, and one bid each of 155 ECU for the bundle I, II, IV and I, III, IV. The auctioneer's revenue will be maximized, if participant D is allocated the bundle I and IV, and participant C is allocated the cards II and III. The remaining bids do not result in any allocations. The overall revenue for the auctioneer is 190 + 80 + 80 = 350 ECU, and participant D receives dividends of 200 ECU. The resulting net reward for this participant is 200 ECU (dividend) minus the successful bid of 190 ECU = 10 ECU. Participant C does not receive any dividends, because cards II and III are not part of the correct solution.

Finally, consider trial 3, displayed in Figure 1. Participant A placed one bid of 99 ECU each for cards I and IV as well as two bids of 151 ECU for the bundle of cards I and IV. Participant B submitted three bids of 50 ECU each for cards I and III as well as one bid of

199 ECU for the bundle of cards I and III.[5] The auctioneer's revenue will be maximized by allocating the bundle of cards I and III to participant B and card IV to participant A. The remaining bids are unsuccessful. The auctioneer's revenue is 199 + 99 = 298 ECU, and neither participant obtains dividends.

These simple examples illustrate several important features of our combinatorial auction. First, trial 1 shows that demand and price are typically positively related; card IV was allocated for only 1 ECU. Participant A was primarily interested in cards I and III, and participant B in cards II and III. Card IV attracted less interest, and was consequently available at a much lower price than cards I, II, and III. Second, bidding for the entire bundle (of all four cards), is seldom optimal, because the bundle cannot be "broken" in the allocation process, which often favors bids on smaller bundles or single cards. Trial 2 shows that participant C was allocated the two cards II and III separately rather than as part of the bundle of cards I, II, III, and IV, although the latter was demanded for at a higher price (180 vs. 80 + 80 = 160 ECU). Finally, trial 3 shows that participants submitting bids for separate cards rather than for bundles are exposed to execution risk. Participant A is allocated only one (card IV) of the desired cards.

Method

We report results of a series of studies designed to determine whether auctions can match the performance level of groups (and outperform individuals) in reasoning problems, and whether these institutions enable their members to successfully transfer knowledge to new (post-interaction) reasoning tasks.

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[5] In fact, the information available regarding participant B on trial 3 is ambiguous (so is the information for participant A on this trial). In case of multiple bids, the screen shown in Figure 1 only displays the mean bid. For the sake of the argument, however, let us assume that participant B submitted three identical bids of 50 ECU each for card I and III.

Considered simultaneously, the various studies define a one-way design, with the single factor reflecting various types of within-group interactions. However, since our studies involve separate institutions and various dependent variables, requiring different units of statistical analysis, we describe and analyze them separately as stand-alone studies. Yet, in the last stage of our analysis, we combine and compare the results of the various institutions in ways that allow us to reach meaningful theoretical conclusions. This joint analysis is justifiable, because (a) the participants in all the studies were from the same population; (b) all the studies were run in the same laboratory by the same experimenter; (c) the studies were conducted in close temporal proximity; and (d) none of the 336 subjects participated in more than one condition.

Each study consists of three independent stages. In the first stage, participants attempt to solve the Wason selection task individually. In the second stage, they interact in a group setting with three other participants (study 1), in a combinatorial auction with three other participants (studies 2 and 3), or in a combinatorial auction individually (study 4). In the third stage, participants are asked to solve new versions of the Wason selection task in an individual setting (see Table 1 for a complete listing of the items used). The purpose of the first stage is to establish solution base-rates and to balance group compositions (see details below).[6] The purpose of the second stage is to compare the effectiveness of different institutional settings in reducing reasoning errors. Finally, in the third stage, we test specific and general knowledge transfers.

Study 1 aims to document learning and knowledge transfers in the Wason selection task in standard face-to-face interacting groups. Study 2 is designed to show similar effects in

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[6] Further support for the joint-analysis stems from the fact that initial solution rates did not differ significantly across the four studies ($\chi^2(3)=4.79$, $p>.05$).

group auctions with individual payoff feedback. Study 3 investigates learning under weaker conditions, withholding individual payoff feedback, and manipulating the level of information available to the bidders. Finally, study 4 allows us to estimate the level of learning and knowledge transfers that can emerge in the absence of interaction.

Study 1: Cooperative group interaction

In this study, we aim to document the beneficial effect of group interaction on the Wason selection task, and to provide a meaningful benchmark for subsequent studies involving competitive auctions.

Experimental design and procedure

Eighty undergraduate students recruited from a large pool of regular study participants were run in groups of 16 participants per session at the Max Planck Research Lab in Jena, Germany.[7] Forty-five females and 35 males, aged 19 to 31 (M=22.80, SD=2.45), participated in the study. Experimental sessions lasted between 75 and 90 minutes. Participants earned, on average, € 7.80 (SD=4.22), including a show-up fee of € 4.

In stage 1, participants solved the first version of the Wason selection task individually (see Table 1) with the understanding that correct choices would be rewarded with € 4. Participants did not receive immediate feedback and payoffs were granted at the end of the experiment.

In stage 2, participants were randomly assigned to groups of four. Groups received written instructions, were accompanied to sound-proof video-cabins, and were asked to solve the second version of the selection task (Table 1). Participants were then instructed to reach a single (binding) group decision within a pre-specified amount of time (30 minutes),[8] and

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[7] Participants in all the studies were from this pool, and all the experiments were run in the same lab.

[8] We allowed for 30 minutes to make this condition as similar as possible with the auctions of studies 2 to 4.

were informed that their interaction would be video- and audio-taped. Correct choices were rewarded with € 4 per person to be paid at the end of the experiment. Participants did not receive immediate feedback.

In stage 3, participants were asked to solve the selection task individually. Forty-eight participants were presented with only one knowledge transfer task (#3, Table 1). We refer to this task, which was administered to all the subjects as specific transfer. The remaining 32 participants saw all eight knowledge transfer items.[9] In the complete set of eight items, the combination (location) of cards constituting the correct solution varied systematically. Each of the six distinct pairs was used once and the "I, IV" pair was used thrice. We refer to the set of all eight items as the general transfer task.

Correct choices in the transfer tasks were rewarded with € 4. When participants were asked to solve eight items, one of them was randomly selected to determine payoffs. At the conclusion of this stage, participants received their cumulative payments and were asked to complete a short questionnaire on socio-demographics.

Results

Stage 1*:* The three most commonly selected card combinations were: cards I and III (40%); card I (25%); and card III (10%). The correct combination, cards I and IV, was chosen by seven participants (9%).

Stage 2: All six groups with at least one individual who had solved the task correctly also solved it correctly at the group level. In the remaining 14 groups, no participant solved the task correctly prior to group interaction. Yet four of these groups identified the correct solution. Overall, 10 of the 20 groups (50%) solved the task correctly.

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[9] The differential number of transfer tasks in stage 3 of this experiment (and also of study 2) was due to the fact that parts of these studies were run in different months. We modified the experimental protocol between these two points of time, to allow for more detailed tests of general knowledge transfers across different tasks.

An analysis of the tapes confirmed that those participants who solved the task in stage 1 successfully convinced the other group members to reconsider their selections and endorse the correct solution. For example, one participant explained to the others: "By selecting only the red card, we cannot be sure whether the rule is correct or wrong. It could be that the card with the rectangle is also red. I think we therefore have to pick both cards." The tapes also shed some light on how correct group choices emerged in those cases where no participant had solved the task individually. Interaction between group members forced subjects to think harder about the problem and to exchange ideas. For example, one participant remarked "Ah, I know the answer. I took a logic course in my first semester and I think this problem is similar to one we solved." Eventually, this person remembered some basic principles of formal logic, allowing the group to apply them to the pertinent task.

Stage 3: To adequately capture knowledge transfers, we restrict our attention to those participants who did not correctly solve the selection task in stage 1. Thirty percent of these subjects solved the first item of the knowledge transfer task (#3, Table 1). Across all eight transfer items, we observed a solution rate of 25%. Interestingly, 28 of the 40 participants who were in groups that solved the problem correctly replicated the correct solution (70%), and only one member (2.5%) of the groups that failed to solve the problem later identified it.

Discussion

We replicated two robust findings: First, only a small percentage of participants solve the Wason selection task correctly. Second, groups perform considerably better than individuals. Half the groups arrived at the correct solution to the task, some doing so even though no single group member had solved the problem initially.

We also provided evidence of positive knowledge transfers from groups to individuals. Thirty percent of the participants who failed to solve the problem initially identified the correct solution after interacting with others. The increase in solution rates for groups and the positive knowledge transfer were, most likely, facilitated by the key features of the group setting. Participants could interact freely with their fellow group members, allowing them to engage in verbal and non-verbal communication.

Interaction in the group setting was non-competitive, so identification of the correct solution by one participant did not affect other participants' payoffs. In the next study, we investigate whether similar learning and knowledge transfers emerge in a more restricted decision environment that involves computerized combinatorial auctions that prevent participants from communicating freely, and introduces competition between participants.

Study 2: Competitive auctions with payoff feedback

In this study we investigate learning and knowledge transfer in competitive auctions that provide individual payoff feedback and allow for information pooling across bidders.

Experimental design and procedure

One hundred twenty-eight undergraduate students were run in groups of 16 participants per session. Sixty-nine females and 59 males, aged 18 to 28 (M=23.00, SD=3.06), participated in the study. Experimental sessions lasted about 120 minutes. Participants earned, on average, € 9.74 (SD=2.15), including a show-up fee of € 2.50.

After participants completed the individual Wason task (stage 1), they were randomly assigned to groups of four. Participants were assigned labels (A, B, C or D), which they kept throughout this stage of the experiment.[10] They were given detailed instructions about the mechanics and functioning of the combinatorial auction. The instructions explained that one can bid for each and any of the 15 possible card combinations of the Wason problem (item #2, in Table 1). After the instructions, subjects participated in two four-minute training

[10] Subjects could not associate these labels with individual participants.

auctions, followed by a short quiz to test their understanding of the trading mechanism. The experiment started only after all participants had answered all the quiz items correctly.

At the beginning of every trial, each participant was endowed with 500 Experimental Currency Units (ECU) to use (as cash) for their bidding.[11] The participants' task was to select the minimal number of cards required to fully test the truth of the target rule. They were instructed to acquire cards they believed to be part of the correct solution. Each complete set of correct cards, i.e. those combinations that included cards I and IV (in addition to, possibly, other cards), was rewarded with dividends of 200 ECU. Successful bids were deducted from these dividends yielding a participant's net reward. To increase competition, we auctioned off only four cards of each type (I, II, III, and IV) on every trial. The procedure used was the one described earlier in the section "the combinatorial auction."

The participants were also informed of the following general rules regarding the auction: (a) endowments cannot be converted to cash at the end of the experiment, (b) the only way to earn money is by acquiring the dividend paying cards, and (c) final payoffs are determined by randomly selecting three auction trials (one from trials 1-10, one from trials 11-20, and one from trials 21-30) and summing up the corresponding net rewards (i.e., dividends minus successful bids).

We ran two experimental conditions that differed in the nature of the payoff feedback provided. In the private-feedback condition (consisting of 20 auctions, n=80), participants were only informed about the outcome of their own bids. If their bids were successful, participants received full information about their dividends and their net rewards at the end of each auction trial. In the public-feedback condition (consisting of 12 auctions, n=48),

[11] One hundred ECU were equivalent to € 1.

participants were also informed about the dividends of the other three participants and their net rewards at the end of each trial.

The experiment consisted of 30 independent auction trials lasting one minute each. After the last auction trial, but prior to the final payment, participants were asked to solve the Wason task individually (stage 3). All 48 participants in the public-feedback condition as well as 48 participants in the private-feedback condition were presented with one transfer item (#3, Table 1). The remaining 32 participants of the private-feedback condition were asked to solve all eight items of the knowledge transfer task (see Table 1). The payoff scheme was identical to study 1. At the conclusion of the experiment, participants received their cumulative payments and were asked to fill in a short questionnaire on socio-demographics.

Results

Stage 1: The three most commonly selected combinations were: cards I and III (34%); card I (34%); and the correct cards, I and IV (14%).

Stage 2: To investigate whether participants learned to acquire the correct cards in the auction, we computed the percentage of correct bids $B_C^{i,t}$ out of the total amount of submitted bids $(500 - cash)$ for each individual i on each auction trial t.[12] Correct bids were defined as bids for the combination of cards I and IV ($B_{I,IV}$), as well as bids for these cards individually (B_I and B_{IV}), when placed at the same time:

$$B_C^{i,t} = \begin{cases} \left[\left(B_{I,IV}^{i,t} + B_I^{i,t} + B_{IV}^{i,t}\right) / \left(500 - cash^{i,t}\right)\right] * 100 \ \ if \ \ B_I^{i,t}, B_{IV}^{i,t} > 0 \ \ or \ \ B_I^{i,t}, B_{IV}^{i,t} = 0 \\ 0 \ \ otherwise \end{cases}$$

[12] We also analyzed an alternative measure to capture learning effects that explicitly contrasts individual preferences for the incorrect card III and the correct card IV. The results reported in this section and in the following two studies were replicated with this alternative measure.

Bids are denoted by B; subscripts indicate card types (I, II, III, or IV), and superscripts denote individuals (i) and trials (t). Consider a few simple examples based on the bids displayed in Figure 1. The proportion of the endowment allocated to correct bids by participant A on trial 1 is 0/500, and 500/500 on trial 3. The corresponding proportions for participant B are 0/500 on trial 1 and 0/499 on trial 3. Finally, the proportions for participants C and D on trial 2 are 160/500 and 190/500, respectively. Note that our definition of correct bids is very restrictive. Even though subjects could obtain dividends by bidding for card combinations that included, in addition to the correct cards, redundant cards, our definition of learning requires subjects to identify the correct cards precisely.

Figure 2 displays the percentage of bids on correct cards across auction trials for both experimental conditions. Since trading behavior in auctions depends on the behavior of all the participants, the unit of statistical analysis is the auction rather than the individual trader. Correct bids $B_C^{i,t}$ were therefore aggregated across the four individual traders in each auction (20 in the private-feedback condition and 12 in the public-feedback condition) and across trial blocks (block 1: trials 1-10, block 2: trials 11-20, block 3: trials 21-30). These aggregated bids were subjected to a 2-way mixed ANOVA with the between-subjects factor "feedback" (public versus private feedback) and the within-subjects factor "auction block" (1, 2, and 3).

The results show significant main effects for feedback ($\underline{F}(1; 30)=26.27$, $\underline{p}<.05$, $\eta^2=.06$) and auction block ($\underline{F}(2; 29)=60.43$, $\underline{p}<.05$, $\eta^2=.10$), as well as an interaction effect ($\underline{F}(2; 29)=3.23$, $\underline{p}<.05$, $\eta^2=.01$). Table 2, which displays the relevant means for the interaction, shows a monotonic increase of correct bids across auction blocks for both experimental conditions. The interaction can be attributed to the fact that the difference in correct bids, between the public- and the private-feedback condition, diminishes over trials.

Stage 3: A majority of those participants who did not solve the original task (stage 1) solved the first item of the knowledge transfer task (#3, Table 1): 51% in the private-feedback condition and 62% in the public-feedback condition. Solution rates were not significantly different in the two conditions ($\chi^2(1)=1.19$, $p>.05$). Across all eight transfer items (only administered in the private-feedback condition), we observed a solution rate of 49%.

Discussion

A market institution that provides swift payoff feedback to traders drastically increased correct responses in the Wason selection task. Although only 14% of the participants solved the selection task correctly in stage 1, bidding behavior in the auctions reflects the correct outcome, evinced by the proportion of correct bids: 74% in the last auction block of the public-feedback condition and 59% in the last auction block of the private-feedback condition.

These high proportions were not achieved instantaneously (see Figure 2). Repeated interaction with fellow auction participants, and the provision of individual payoff feedback, was necessary to allow for information dissemination and aggregation.[13] The significant interaction effect indicates that learning of the correct solution steadily increased, with differences between the two conditions diminishing with experience. We also observed impressive knowledge transfers from auctions to individual behavior. The higher proportions of bids for the correct solution, and the positive knowledge transfer, were caused by two independent mechanisms that impact the market: payoff feedback provided to traders, and information spillovers from those who knew the correct solution to those who did not. Study 2 showed that when both mechanisms operate, the auction reflects the correct outcome.

[13] This joint effect of individual and social learning is consistent with the results reported in a different context by Kameda and Nakanaishi (2002, 2003).

In the next study, we investigate whether similar learning effects and knowledge transfers emerge in a much weaker setting without trial-by-trial payoff feedback. To test for information spillovers, we inform a subset of traders about the correct outcome to the problem and study whether information pooling allows the uninformed traders to infer the correct solution.

Study 3: Competitive auctions without payoff feedback

Experimental design and procedure

Ninety-six undergraduate students were run in groups of 16 participants per session. Sixty-nine females and 27 males, aged 19 to 32 (M=22.39, SD=2.67), participated in the study. Experimental sessions lasted about 120 minutes. Participants earned, on average, € 8.03 (SD=2.25), including a show-up fee of € 2.50.

The basic auction setup was the same as in study 2. The main difference pertains to the manipulation of informed participants. These "insiders" were explicitly told which cards made up the correct solution in stage 2 of the experiment. We ran three experimental conditions with zero, one, or two informed participants. Each experimental condition consisted of eight groups of four subjects (n=32). All participants who solved the task correctly in stage 1 were assigned the role of insiders. The remaining insider roles were filled randomly. Insiders maintained their status throughout the experiment, and were reminded of the correct solution at the beginning of each auction trial. Uninformed participants ("outsiders") were neither informed about the existence of insiders in the auctions nor privy to any feedback about dividend payments between trials.

Results

Stage 1: The three most commonly selected card combinations were: cards I and III (49%); card I (20%); and the correct cards, I and IV (7%).

Stage 2: Figure 3 displays the percentage of correct bids across auction trials. The left panel summarizes all the bids (by the informed and uninformed bidders) and the right panel displays only the bids of the uninformed "outsiders." We analyzed the percentage of cash that was bid on the correct cards (B_C) by the uninformed "outsiders" in a 2-way mixed ANOVA with the between-subjects factor number of "insiders" (0, 1, and 2) and the within-subjects factor "auction block" (1, 2, and 3). The results show significant main effects for the number of insiders ($F(2; 21)=7.84$, $p<.05$, $\eta^2=.11$) and auction block ($F(2; 20)=5.06$, $p<.05$, $\eta^2=.01$), but no interaction between the two. Tukey's HSD post-hoc tests (at the .05 level), show a significantly higher percentage of correct bids in the conditions with (one and two) insiders as opposed to the condition without informed traders.

Stage 3: Among the subjects who did not solve correctly the task in stage 1 and who were not selected as insiders in stage 2, 6% solved the first item of the knowledge transfer task (#3, Table 1) in the condition with zero insiders, 17% in the condition with one insider, and 19% in the condition with two insiders. Solution rates are monotonically related to the number of insiders, but did not vary significantly across conditions ($\chi^2(2)=2.10$, $p>.05$). Across all eight transfer items, we observed 7% correct choices in the condition with zero insiders, 15% correct choices in the condition with one insider, and 23% correct choices in the condition with two insiders. The three mean values are not significantly different ($F(2; 69)=0.73$, $p\geq.05$), although they increase as a function of the number of insiders.

Discussion

The purpose of this study was to test whether convergence to the correct solution, and positive knowledge transfers from auctions to individuals, can be achieved in the absence of individual payoff feedback through information spillovers from those traders who knew the correct solution to those who did not.

It appears that the bidding behavior of the uninformed participants was systematically influenced by the insiders' bidding behavior. We observed a significantly higher percentage of correct bids by the uninformed traders when they interacted with at least one informed participant as compared to the baseline condition, consisting only of uninformed participants. This finding is even more impressive, considering that the uninformed traders were not even aware of the existence of the informed traders.

We also observed pronounced levels of positive knowledge transfers from auctions to individual behavior, considering that the baseline of correct solutions in this task is around 10%. We also found a positive and monotonic relation between the percentage of correct solutions in the transfer items and the number of informed traders, subjects interacted with, in the auctions.

The first three studies demonstrated that reasoning in the Wason selection task can be improved considerably by allowing participants to share and pool information in various interactive settings, ranging from standard face-to-face group interactions with aligned incentives to competitive auctions allowing for payoff feedback and/or information spillovers among bidders. To put these results in the proper perspective, we ran a control condition in which we allowed participants to learn the solution to the Wason task individually, using a process similar to the auctions.

Study 4: Non-competitive auctions with payoff feedback

This study provides a control that allows us to estimate the level of knowledge transfers that can emerge in the absence of interaction. To make it as similar to the other studies as possible, subjects took part in individual auctions with trial-by-trial payoff feedback.

Experimental design and procedure

Thirty-two undergraduate students (21 females and 11 males, aged 21 to 30 (M=22.59, SD=2.79)), participated in the study. Experimental sessions lasted about 120 minutes. Participants earned, on average, € 8.63 (SD=2.26), including a show-up fee of € 2.50.

The basic auction setup was identical to the setup of studies 2 and 3, but participants placed bids for solution cards individually (see Figure 4 for a schematic screen shot of the auction). The absence of competition, of course, implies that subjects could acquire the cards at extremely low prices. A comparison with studies 2 and 3, however, is still possible since the variable of interest (B_C) is based on the proportion of correct bids out of all bids. Finally, all participants saw all eight knowledge transfer items in stage 3 of the experiment.

Results

Stage 1: The three most commonly selected card combinations were: cards I and III (25%); card I (22%); and the correct cards, I and IV (19%).

Stage 2: We are not interested in the details of the individual bidding behavior. For our purpose it suffices to concentrate on the proportion of bids submitted for the correct cards in the last auction block, which was 42%. The fraction of correct bids on each trial is displayed in Figure 5.

Stage 3: Eleven of the 26 participants (42%), who did not solve the task correctly in stage 1, picked the correct cards in the first transfer task. Across all eight transfer items, 38% of the responses were correct.

Discussion

The results indicate that a substantial proportion of participants learned to identify the solution to the Wason task, after participating in an individual non-competitive auction, and exhibited positive knowledge transfers from the auctions to individual behavior.

Synopsis

In this section, we compare the effectiveness of the various interactive institutions (of studies 1 to 3) in improving reasoning in the Wason selection task by jointly analyzing the results of the various studies. In these analyses, we differentiate between the interactive stage and the knowledge transfer stage.

Information pooling and group convergence (Stage 2): We define a variable that indicates whether "group" j (i.e., 20 groups in study 1; 32 auctions in study 2; 24 auctions in study 3) identified the correct solution by the end of the interaction. In each auction, we define a "success" (which was assigned a value of 1) if the total amount of bids for the correct cards (I and IV) exceeded the total amount of bids for the incorrect cards (II, III) on the final trial (t=30), and a "failure" (assigned a value of 0) otherwise. For the 20 groups in study 1, we defined the variable similarly (i.e., 1 if the group identified the correct outcome, 0 otherwise).[14] The second column in Table 3 displays the number and percentages of groups that reached the correct solution by the end of their interactions for all conditions.

A comparison of these proportions by means of a χ^2 exact test indicates that the levels of group convergence on the correct choice varied across institutions ($\chi^2(5) = 15.87$; $p < 0.05$). Post-hoc tests that control the experimentwise error rate at 0.05 show that convergence to the correct solution rates were significantly higher in the two conditions with payoff feedback (private and public), and in the group setting, than in the baseline treatment (with zero insiders).

Specific knowledge transfer (Stage 3): We compared the level of positive transfers on the first item (#3, Table 1) among those subjects who neither solved the task correctly in stage 1

[14] We recognize that the two measures are not, strictly speaking, indentical. They are, however, comparable. We take the fact that a majority of the bids in a given session are placed on the correct solution as a proxy for a majority vote in favor of this solution by the group.

nor were assigned the role of insiders in stage 2. The results (displayed in column 3 of Table 3) indicate that solution rates differ significantly across the experimental conditions ($\chi^2(6)=29.70$, $p<.05$). Post-hoc tests that control the experimentwise error rate at 0.05 show that transfer rates were significantly higher in the two conditions with payoff feedback (private and public), and in the group setting, than in the baseline treatment (with zero insiders).

General knowledge transfer (Stage 3): Finally, we analyzed knowledge transfers across all eight items for the subset of participants, who received the longer questionnaire, and who neither solved the task correctly in stage 1, nor were informed about the correct solution in stage 2. We calculated the proportion of correct solutions, T_i, for each individual i. This index ranged from 0 (none of the items answered correctly) to 1 (all eight items answered correctly). We performed a one-way ANOVA with T_i as dependent variable, and found significant differences between the experimental conditions ($F(5; 155)=4.40$, $p<.05$, $\eta^2=.12$; see Table 3, last column). Tukey's HSD post-hoc tests (at the .05 level) indicate that the proportion of correct solutions was higher in the private-feedback condition than in the conditions with zero insiders and one insider.

General discussion

Group decisions are ubiquitous in business, politics, law, education, and industry. Previous empirical work by social psychologists has shown that groups usually perform better than individuals in simple intellective tasks, and this body of research has documented specific and general knowledge transfers from groups to individual decision makers. One pivotal feature of these findings is the cooperative nature of standard group interactions. In this paper we asked whether cooperation is, indeed, necessary to achieve these beneficial effects of groups.

Research by economists has shown that competitive markets allow for dissemination and aggregation of information, even though individual traders have strong incentives to withhold it. To exploit their private information, participants must act on it, thereby revealing (at least part of) it to the other market participants. Unlike prior work that illustrated the effectiveness of markets in judgmental contexts such as winners of political elections (Forsythe et al., 1992), and entertainment awards (Pennock et al., 2001), we focused on a purely intellective task and imported the idea of competitive markets as information pooling institutions to a well-known reasoning problem. Our studies allow us to compare performance in the Wason selection task at the individual and aggregate level, to contrast cooperative groups and competitive auctions, and to study specific and general knowledge transfers.

Table 3 summarizes the results of the various stages of all the studies. The first column shows that only 11% of the 336 subjects solved the problem correctly. The second column displays the percentage of correct solutions for interactive groups and competitive auctions on the last trial of stage 2. The rows of the table are ordered according to the magnitude of these values, ranging from the auctions with public feedback to the auctions with no feedback and no information. The last two columns include the rates of specific (the one item that was presented in stage 1) and general (8 different items) transfer as measured in stage 3. Both are calculated only for those subjects who did not solve the problem correctly in stage 1, and were not informed about the correct solution in stage 2. Note the close correspondence between the rate of (group) convergence (stage 2) and the rates of specific and general knowledge transfer (stage 3).

Our results indicate that (a) interactive cooperative groups, competitive auctions, and individuals who receive swift payoff feedback, learned the solution to the problem and performed better than individuals. We (b) uncovered specific and general knowledge transfers from these institutions to new reasoning tasks. A comparison of the various institutions indicates that (c) auctions with public payoff feedback outperformed all the others in the interactive stage. Finally, we (d) found that auctions with payoff feedback, as well as standard groups, amplified the specific knowledge transfer, and that payoff feedback increased the general knowledge transfer, as compared to the baseline-treatment. In most conditions the rate of specific transfer is higher than the rate of general transfer, and both are higher than the rate of spontaneous correct solutions in stage 1.

The key commonality of groups and auctions is that both provide the necessary conditions for the emergence of a shared mental model of the problem. This is quite obvious in the case of the interacting groups but, somewhat surprisingly, applies to competitive institutions as well. In fact, Mantzavinos, North and Shariq (2003), claim that "Institutions are shared behavioral regularities … [and] are nothing more than shared mental models or shared solutions to recurrent problems of social interaction" (page 7).

In groups the shared models emerge from free communication among all their members, who share common goals. Auctions attain similar effects even in the absence of direct communication among the competing members. We argued that despite the difference between the groups' cooperative nature and the auctions' competitive nature, auctions meet four of the postulates stipulated for collective induction in groups (Laughlin, 1999): a conceptual system with known rules and terminology (4a), sufficient information (4b), ability to recognize the solution to a problem (4c), incentives for correct solutions (3 and 5), and aggregate solutions comparable in quality to the best (of a similar number) of individuals (9).

Research on groups has underscored the importance of identifying the best members in the group to facilitate collective induction. Critical conditions for such identification are loquacity, use of reason to influence, autocracy, dominance, and member confidence (Littlepage & Mueller, 1997; Littlepage, Schmidt, Whisler, & Frost, 1995), as well as the reception of regular performance outcome feedback (Henry, Strickland, Yorges, & Ladd, 1996). The corresponding features of markets are the sustainability and consistency of individual trading behavior (bids, volume, etc.), as well as publicly available information about trading earnings (e.g., the public-feedback condition in study 2). These allow traders to identify the most desirable assets and the most successful trading strategies.

Our results suggest that auctions could help overcome some of the problems and limitations of interacting groups. Research on “hidden profiles” (Stasser & Titus, 1985), for instance, indicates that groups focus on, and discuss, shared information at the expense of unshared information, leading to suboptimal outcomes (failure to uncover hidden profiles). One explanation is that in this context the participants lack appropriate incentives to fully and properly share information. Competitive auctions, populated by traders with the desire to increase individual payoffs, could considerably reduce such partial information revelation through monetary incentives. This is in sharp contrast to recent findings by Hollingshead et al. (2005) who documented the detrimental effects of competition in interacting groups. When some of the participants had differential incentives, they engaged in information distortion and strategic information sharing. The auctions are largely immune to such manipulations and, for all practical purposes, serve as a truth revealing mechanism (for failed attempts at manipulating markets see Camerer, 1998; and the discussion by Wolfers and Zitzewitz, 2004).

Finally, whereas several studies show either no performance advantage for “electronic group interaction” (Straus & McGrath, 1994) or some disadvantage (Hollingshead, McGrath, & O’Connor, 1993), we find that computerized auctions lead to performance improvements and knowledge transfers comparable to standard face-to-face groups.

Future research should extend the contrast between cooperative and competitive decision settings by testing the predictions of the social decision scheme theory (Davis, 1973) and the theoretical framework of collective induction (Laughlin, 1999). For example, it would be interesting to compare judgmental and intellective tasks, study the relative importance of multiple hypotheses and multiple evidence (Laughlin & McGlynn, 1986), or preferences for confirmatory and disconfirmatory hypotheses (Laughlin, Magley, & Shupe, 1997). Research in these areas would help to determine if, and to what extent, well-established empirical findings on cooperative groups generalize and translate to competitive settings. It would also foster our understanding of the fundamental similarities and differences between these institutions.

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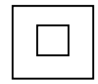
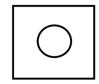
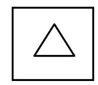
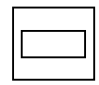
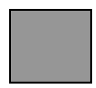
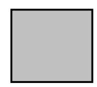
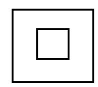
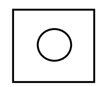
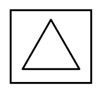
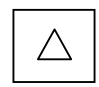
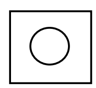
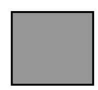
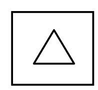
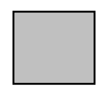
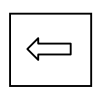
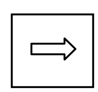
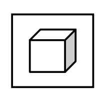
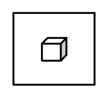
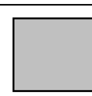
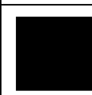
Table 1: <u>Materials Used in Studies 1-4 (Solution cards)</u>

	Cards			
Stage 1:	I	II	III	IV
1. If the card is blue on one side, then there is a square on the other side. (I, IV)				
Stage 2:				
2. If the card is red on one side, then there is a triangle on the other side. (I, IV)				
Stage 3:				
3. If the card is blue on one side, then there is a square on the other side. (I, IV)				
4. If there is a small triangle on one side, then there is a $-symbol on the other side. (III, IV)	$		£	
5. If there is a vowel on one side, then there is an even number on the other side. (II, III)	K	E	7	2
6. If there is a circle on one side, then the card is yellow on the other side. (I, II)				
7. If there is an arrow that points to right on one side, then there is a large cube on the other side. (II, IV)				
8. If the card is grey on one side, then there is an &-symbol on the other side. (I, III)		&	§	
9. If a person gets a bonus, she must have sold more than 125 units. (I, IV)	Bonus	> 125	No Bonus	< 125
10. If a person drinks alcohol, she must be older than 21 years of age. (I, IV)	Beer	Cola	21 yrs	16 yrs

Note: Correct card combinations are shown in parentheses.

Table 2: Means and Standard Errors of the Rate of Correct Bids as a Function of Feedback and Block (Study 2)

Feedback	Block	Mean	Standard error
Private	1 (trials 1-10)	24.39	1.56
	2 (trials 11-20)	50.19	1.74
	3 (trials 21-30)	58.60	1.68
Public	1 (trials 1-10)	52.25	2.30
	2 (trials 11-20)	67.01	2.18
	3 (trials 21-30)	74.28	1.90

Table 3: Solution Rates by Experimental Condition and Experimental Stage

Institution	Experimental stage Stage 1	Stage 2	Stage 3 (one item)	Stage 3 (all items)
Auctions with public feedback	9/48 = 19%	10/12 = 83%	24/39 = 62%	-
Auctions with private feedback	9/80 = 11%	11/20 = 55%	36/71 = 51%	142/288 = 49%
Interactive groups	7/80 = 9%	10/20 = 50%	28/73 = 38%	146/584 = 25%
Auctions without feedback (interacting with two insiders)	1/32 = 11%	3/8 = 38%	3/16 = 19%	29/128 = 23%
Individual auctions	6/32 = 19%	11/32 = 34%	11/26 = 42%	80/208 = 38%
Auctions without feedback (interacting with one insider)	6/32 = 19%	2/8 = 25%	4/24 = 17%	29/192 = 15%
Auctions without feedback and no interaction with insiders	0/32 = 0%	0/8 = 0%	2/32 = 6%	19/256 = 7%
Total	38/336 = 11%	47/108 = 44%	108/281 = 38%	445/1656 = 27%

Notes:

Stage 1: Percentage of subjects who solved the problem correctly

Stage 2: Percentage of groups / auctions that solved the problem correctly on the last trial

Stage 3 (1 item): Percentage of subjects who neither solved the problem correctly in the first stage, nor were informed about the correct solution in the second stage, but answered correctly the first transfer item.

Stage 3 (8 items): Percentage of transfer items answered correctly by subjects who neither solved the problem correctly in the first stage, nor were informed about the correct solution in the second stage.

Figure Captions

Figure 1. Schematic Screen Shot of the Combinatorial Auction (Studies 2 and 3)

Figure 2. Percentage of Correct Bids (and Standard Errors) in the Two Feedback Conditions (Study 2)

Figure 3. Percentage of Correct Bids (and Standard Errors) as a Function of the Number of Informed Bidders (Study 3)

Figure 4. Schematic Screen Shot of the Combinatorial Auction (Individual Control Study)

Figure 5. Percentage of Correct Bids (and Standard Errors) in the Individual Control Study

Figure 1. Schematic Screen Shot of the Combinatorial Auction (Studies 2 and 3)

You are PARTICIPANT C Trial 4 Seconds 9

Participant A

Mean Bid (Quantity) in Trial

Combination	1	2	3	Current
I	-	-	99 (1)	-
II	-	-	-	-
III	-	-	-	-
IV	-	-	99 (1)	-
I, II	-	-	-	-
I, III	190 (1)	-	-	-
I, IV	-	-	151 (2)	-
II, III	-	-	-	-
II, IV	-	-	-	-
III, IV	-	-	-	-
I, II, III	155 (1)	-	-	-
I, II, IV	-	-	-	-
I, III, IV	155 (1)	-	-	-
II, III, IV	-	-	-	-
I, II, III, IV	-	-	-	-

Participant B

Mean Bid (Quantity) in Trial

Combination	1	2	3	Current
I	-	-	50 (3)	-
II	70 (1)	-	-	-
III	69 (1)	-	50 (3)	-
IV	1 (1)	-	-	-
I, II	-	-	-	-
I, III	-	-	199 (1)	-
I, IV	-	-	-	-
II, III	180 (1)	-	-	-
II, IV	-	-	-	-
III, IV	-	-	-	-
I, II, III	-	-	-	-
I, II, IV	-	-	-	-
I, III, IV	-	-	-	-
II, III, IV	-	-	-	-
I, II, III, IV	180 (1)	-	-	-

Combination	Price	Quantity
I		
II		
III		
IV		
I, II		
I, III		
I, IV		
II, III		
II, IV		
III, IV		
I, II, III		
I, II, IV		
I, III, IV		
II, III, IV		
I, II, III, IV		

Your cash holdings:
401

SUBMIT

Participant C

Mean Bid (Quantity) in Trial

Combination	1	2	3	Current
I	-	80 (1)	-	99 (1)
II	-	80 (1)	-	-
III	-	80 (1)	-	-
IV	-	80 (1)	-	-
I, II	-	-	-	-
I, III	-	-	-	-
I, IV	-	-	-	-
II, III	-	-	-	-
II, IV	-	-	-	-
III, IV	-	-	-	-
I, II, III	-	-	-	-
I, II, IV	-	-	-	-
I, III, IV	-	-	-	-
II, III, IV	-	-	-	-
I, II, III, IV	-	180 (1)	-	-

Participant D

Mean Bid (Quantity) in Trial

Combination	2	3	4	Current
I	-	-	-	-
II	-	-	-	-
III	-	-	-	-
IV	-	-	-	-
I, II	-	-	-	-
I, III	-	-	-	-
I, IV	-	190 (1)	-	-
II, III	-	-	-	-
II, IV	-	-	-	-
III, IV	-	-	-	-
I, II, III	-	-	-	-
I, II, IV	-	155 (1)	-	-
I, III, IV	-	155 (1)	-	-
II, III, IV	-	-	-	-
I, II, III, IV	-	-	-	-

Figure 2. Percentage of Correct Bids (and Standard Errors) in the Two Feedback Conditions (Study 2)

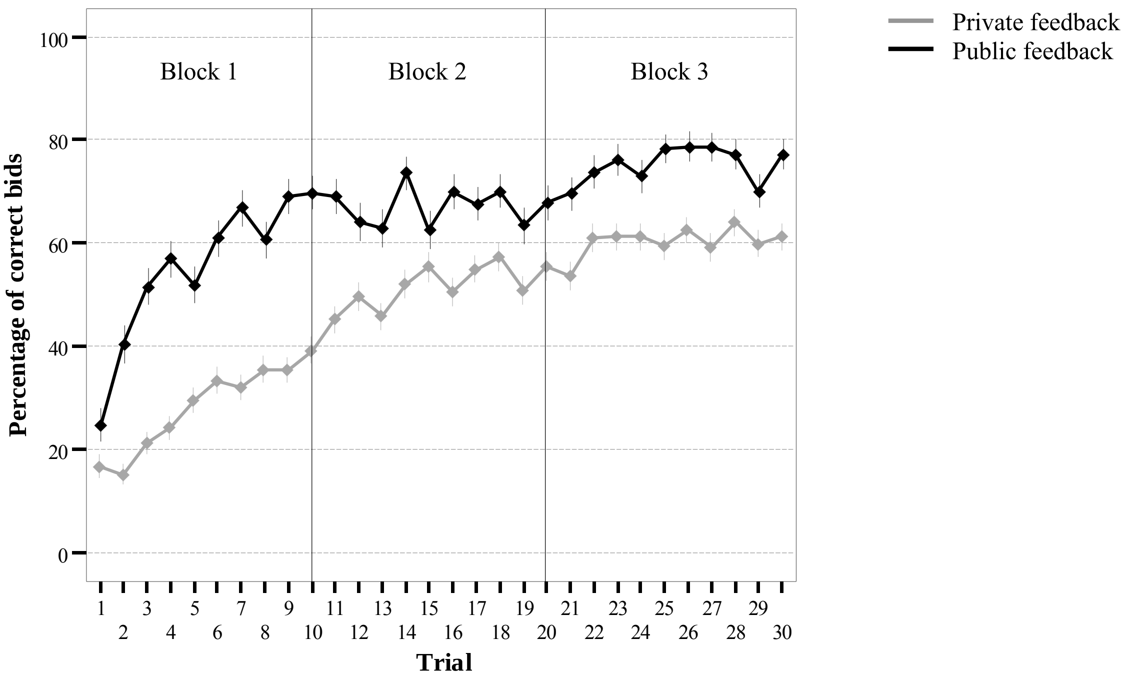
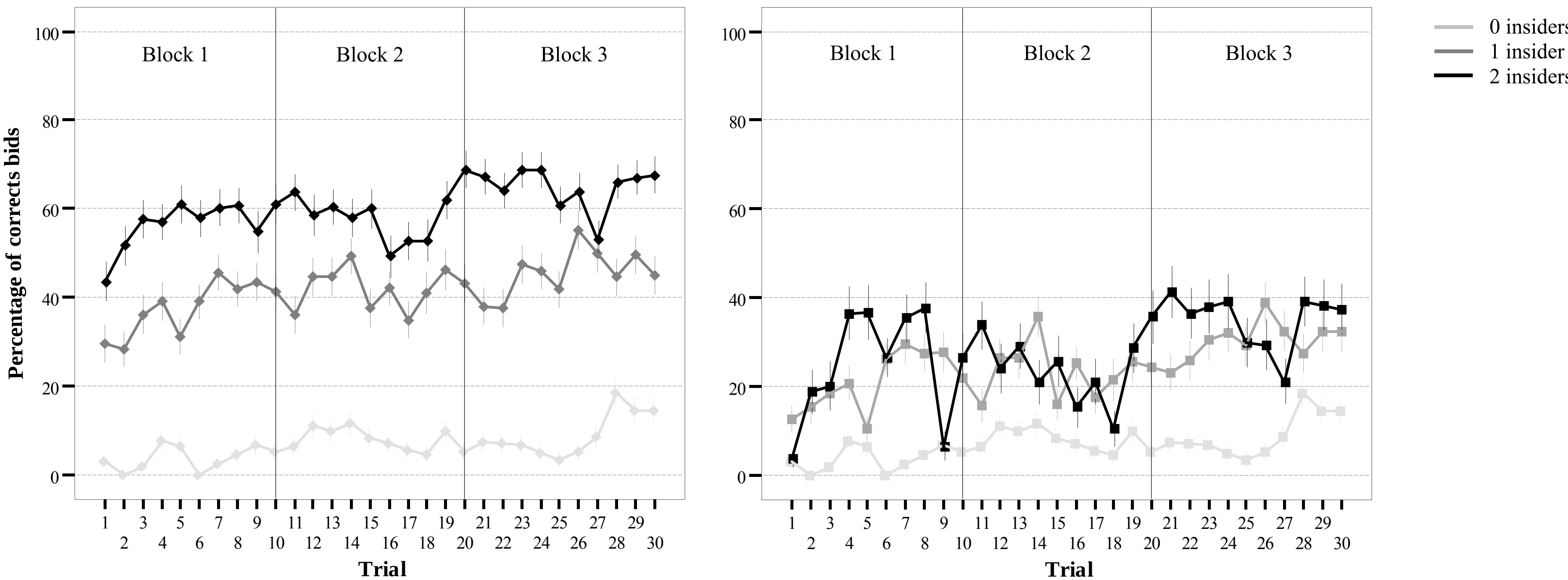


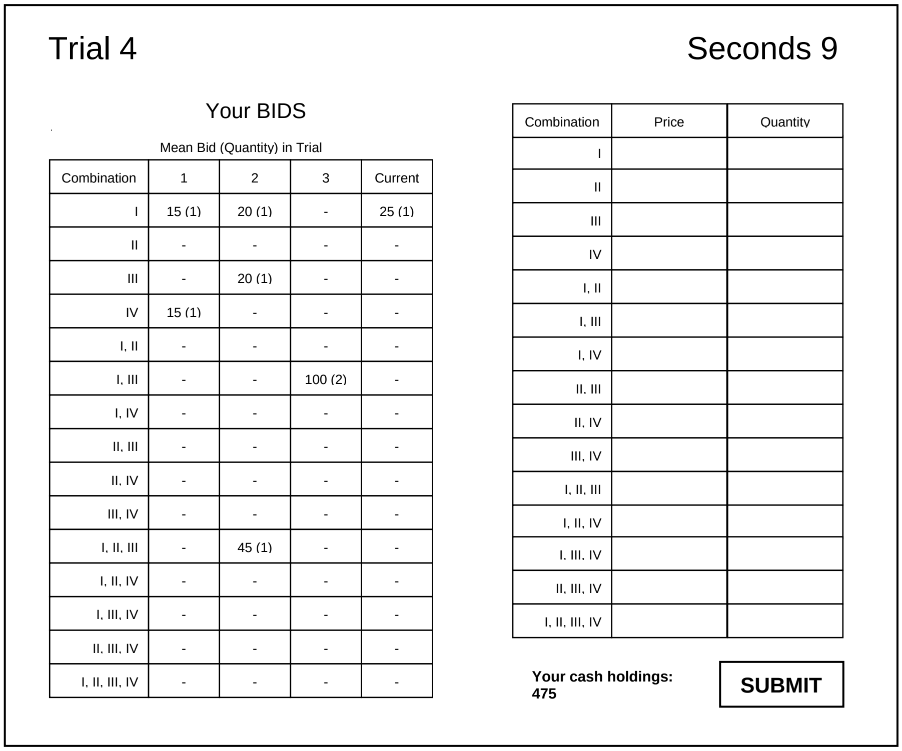
Figure 3. Percentage of Correct Bids (and Standard Errors) as a Function of the Number of Informed Bidders (Study 3)



a: Bids by insiders and outsiders

b: Bids only by outsiders

Figure 4. Schematic Screen Shot of the Combinatorial Auction (Individual Control Study)



Combination	1	2	3	Current
I	15 (1)	20 (1)	-	25 (1)
II	-	-	-	-
III	-	20 (1)	-	-
IV	15 (1)	-	-	-
I, II	-	-	-	-
I, III	-	-	100 (2)	-
I, IV	-	-	-	-
II, III	-	-	-	-
II, IV	-	-	-	-
III, IV	-	-	-	-
I, II, III	-	45 (1)	-	-
I, II, IV	-	-	-	-
I, III, IV	-	-	-	-
II, III, IV	-	-	-	-
I, II, III, IV	-	-	-	-

Combination	Price	Quantity
I		
II		
III		
IV		
I, II		
I, III		
I, IV		
II, III		
II, IV		
III, IV		
I, II, III		
I, II, IV		
I, III, IV		
II, III, IV		
I, II, III, IV		

Figure 5. Percentage of Correct Bids (and Standard Errors) in the Individual Control Study