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Teams Make You Smarter: How Exposure to Teams Improves Individual Decisions in Probability and Reasoning Tasks

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Many important decisions are routinely made by transient and temporary teams, which perform their duty and disperse. Team members often continue making similar decisions as individuals. We study how the experience of team decision making affects subsequent individual decisions in two seminal probability and reasoning tasks, the Monty Hall problem and the Wason selection task. Both tasks are hard and involve a general rule, thus allowing for knowledge transfers, and can be embedded in the context of markets that offer identical incentives to teams and individuals. Our results show that teams trade closer to the rational level, learn the solution faster, and achieve this with weaker, less specific performance feedback than individuals. Most importantly, we observe significant knowledge transfers from team decision making to subsequent individual performances that take place up to five weeks later, indicating that exposure to team decision making has strong positive spillovers on the quality of individual decisions.

Key words: markets; group decision making; Wason selection task; Monty Hall dilemma; team decision making
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1. Introduction

Many important decisions that, in principle, could be made by individuals are routinely made by teams. These include strategic decisions (e.g., boards of directors deciding in which markets to compete), allocation decisions (e.g., committees deciding on budgets), merit-based forecasting decisions (e.g., scientific panels deciding which research proposals to fund), intellective decisions (e.g., committees solving complex problems), and judgmental decisions (e.g., juries judging musical, literary, sport, and beauty contests).

Most of these decisions are made by teams that are transient and temporary, being assembled by an external coordinator or supervisor or congregating spontaneously and voluntarily for a short duration, ranging from a few days (jury in a trial or a musical contest) to a few years (scientific review boards or directors of a company). These teams perform their duty and then disperse. Members are frequently selected based on their qualifications, experience, or expertise, and often continue to make similar decisions as individuals when their service on the team is concluded. Although there is considerable research comparing the nature and quality of the decisions made by teams and individuals (for recent reviews, see Charness and Sutter 2012, Kugler et al. 2012), relatively little is known about the effects of being on a team on subsequent individual decisions. However, because teamwork is ubiquitous in organizations, it is highly relevant, and potentially very beneficial, for companies to learn whether team decision making has a positive impact on the decision making of individuals.

In this paper, we study whether being part of a team is beneficial beyond the actual interaction by investigating individual performance of former team members up to five weeks after the team interaction took place. We use two seminal intellective tasks—a probability judgment task (the Monty Hall problem) and a reasoning task (the Wason selection problem). To offer unambiguous and identical incentives to teams and individuals, we implement these tasks in a market setting where potential solutions to the task can be traded as assets.

Our results show that teams outperform individuals in the market and in subsequent individual tasks (even five weeks after the interaction). Specifically, teams are more strategic than individuals (e.g., they employ a hedging strategy), price the assets closer to the rational level, learn the solution to the task faster, and achieve this with weaker, less specific performance feedback. Some teams even perform better than their best individual members. We also observe knowledge transfers in subsequent individual performance of up to five weeks later. Our analysis rules out the possibility that the superiority of the teams is due to their size or extra information, and an analysis of the content of the within-group interactions suggests that many teams engage in the strategic elimination of incorrect solutions.

This paper is organized as follows: In §2 we highlight the contribution of our work to the literature on individual and team decisions. In §3 we introduce our experimental design and materials. Sections 4 to 6 present three experimental studies. Section 7 offers an analysis and a discussion of our results. Section 8 concludes the paper.

2. Contribution to the Literature on Teams vs. Individuals

Previous research indicates that, in general, teams perform better than individuals in nonstrategic tasks (Tindale et al. 2003) and make more self-interested choices in strategic games, driving team decisions in these games closer to the standard equilibrium predictions (Charness and Sutter 2012). For instance, teams are better in solving intellective tasks (e.g., Laughlin 1980) and are better calibrated in assessing their knowledge (Allwood and Granhag 1996). Teams have also been shown to be more competitive in prisoner's dilemma games (Wildschut et al. 2003), to play more strategically in signaling games (Cooper and Kagel 2005), and to coordinate more efficiently than individuals in coordination games (Feri et al. 2010).

The superiority of teams, or groups more generally, compared to individuals has been explained by social-decision scheme theory (Davis 1973), which describes group interaction as a combinatorial process that aggregates individual preferences to reach consensual group choices (Tindale et al. 2003). For tasks that have a demonstrably correct solution, the theory predicts "truth wins" (Davis 1992). Thus, if the correct solution can be demonstrated to fellow group members, they will eventually endorse it, and the group will perform at the level of its best individual member. Evidence supporting this prediction includes rule-induction problems (Laughlin et al. 1998), letters-to-numbers problems (Laughlin et al. 2002), and Mastermind problems (Bonner et al. 2002). In some tasks, groups even outperform the best individual member (Cooper and Kagel 2005; Laughlin et al. 2003, 2006).

Given that, everything else being equal, teams perform better than individuals, we seek to test whether the superiority of team membership has longer-term consequences and carries over to postinteraction individual behavior. To put it differently, we seek to establish that tackling a task as part of a team causes people to analyze it better and learn to solve it more effectively, allowing us to quantify the "benefits of team membership" for subsequent individual decision making. Team structures and knowledge transfers have become increasingly important in organizations (Argote et al. 2000, Salas et al. 2008), leading to more employee involvement and satisfaction (Wellins et al. 1994) and to improved performance (Salas et al. 2007). Despite this interest in team decision making, relatively little is known about the effects of being on a team on subsequent individual decisions. Cooper and Kagel (2005) showed that teams are better able to transfer knowledge from one game to another, but they did not address whether the experience of team decision making improves subsequent individual decision making.

In this paper, we combine approaches and insights from behavioral economics and social and cognitive psychology to study the effects of team decision making on subsequent individual decisions. We are doing so by embedding intellective tasks in competitive markets. Budescu and Maciejovsky (2005) showed that such markets allow their participants to learn the solution to an intellective problem and to transfer it to a set of new problems. Maciejovsky and Budescu (2007) showed that learning—and knowledge transfer rates—in competitive markets are similar to the rates observed in face-to-face interactive groups that perform in a noncompetitive, nonmarket setting. Maciejovsky and Budescu (2007) pointed out that, somewhat surprisingly, interacting teams in noncompetitive settings and individuals in competitive markets share many features that cause both to develop similar mental models. However, in that paper, both settings—the *interaction format and* the *incentive structure*—differed, confounding their respective effects. More specifically, individuals traded anonymously and without direct communication on markets with competitive incentives, whereas teams with aligned incentives (all payoffs are identical for all the members) discussed potential solutions face-to-face without competing against other teams.

In the current paper, we disentangle this confound by fixing the incentive structure and by comparing trading behavior of individuals and teams on *identical markets* and with *identical incentives*. Thus, whatever differences we uncover on and after the market, when all subjects make individual decisions again, can be unambiguously attributed to differences between the two entities—individuals and teams—and the distinctive nature of the within-team interaction, which, of course, is absent on markets with individual traders. In addition to studying learning transfer from team to individual decision making under such carefully controlled conditions, our paper is also novel in that it is the first to examine how persistent such team-to-individual transfers of knowledge are. This issue is particularly important for organizations that can benefit from medium- and long-term effects of exposure to team decision making on individual performance.

3. The Present Studies

We report the results of three studies. In Study 1 we investigate whether teams use a more strategic approach (i.e., a hedging strategy) to a probability problem (the Monty Hall problem) than individuals in a competitive market, and whether the transfer of knowledge from team to individual decisions persists over several weeks. In Studies 2a and 2b we seek to determine whether teams learn the solution to a reasoning problem (the Wason selection task) faster than individuals and whether they are more successful in transferring their skills to a set of new problems, which are tackled individually. Finally, in Study 3 we test whether teams require weaker and less specific performance feedback to achieve these outcomes.

All three studies share a common structure consisting of three independent stages and two different tasks. In the first study, we use the Monty Hall problem (named after the 1960s TV game show host of *Let's Make A Deal*). In the second and third studies, we use the Wason selection task (which is "the single most investigated problem in the psychology of reasoning," according to Evans and Over 1996, p. 356). Participants were asked to solve the Monty Hall/Wason selection problem individually in the first stage. In the second stage participants traded potential solutions to the Monty Hall/Wason selection problem in auctions and markets (more details later). On these markets participants either interacted individually with three other individuals or as part of two-person teams with three other two-person teams. In the third stage, participants were asked to solve new versions of the Monty Hall/Wason selection problem individually. In Study 1 there was a fourth stage, in which participants were asked to solve new Monty Hall problems five weeks after the market experiment, allowing us to examine the persistence of knowledge transfer. Next we discuss why markets might help traders to solve intellective tasks, and then we introduce the Monty Hall problem and the Wason selection task.

3.1. Markets as a Learning Tool

Camerer (1987) listed a number of economic forces that might allow markets to cancel out individual biases and noise. Among these factors is the provision of clear and unambiguous incentives, the ability of biased traders to infer information from less biased traders through feedback (Budescu and Maciejovsky 2005), and the disproportionate impact of a small number of unbiased traders (with enough access to capital) to impact prices. Learning is facilitated through observing bids, asks, and trades that all convey information about the underlying assets (Bloomfield et al. 1996, Meloso et al. 2009).

Because markets are characterized by a set of rigid rules, designed to standardize interactions and communications among participants (Maciejovsky and Budescu 2013), they offer a potential learning tool allowing participants to infer the solution to problems with unique solutions. Participants can, for instance, reassess their solutions and valuations by taking into account the number and magnitude of bids or asks that have been submitted for specific solutions, make inferences based on trading prices for different solutions, consider payoff feedback received between market periods, etc. We now introduce the two intellective tasks used in our studies.

3.2. The Monty Hall Problem

We use a variant of the problem that involves playing cards (following Friedman 1998, Kluger and Wyatt 2004). We showed participants three stylized playing cards (marked with the suits *clubs*, *diamonds*, and *hearts*). We also endowed participants with one card (randomly selected from the three). All participants were given the same suit. For exposition purposes, assume that the suit hearts was picked. Participants were then shown the three cards, facedown, in random order (labeled 1 to 3). A number (1 to 3) was randomly determined and the corresponding card was set aside (still facedown).

Participants were told that, because they held a heart card, they would receive £1 if the set-aside card was a heart card and £0 otherwise. However, they also had the option of switching from the original card (heart) to one of the other cards after one of the two remaining cards was revealed. Note that the revealed card was always a losing card, i.e., given the endowment of a heart card in our example, the losing card must have been either a club or a diamond card. For exposition, assume that a diamond card was revealed.

After the card revelation, participants had to decide whether they wanted to switch (from a heart card to a club card[1]). They were promised £1 if the set-aside card matched the one they had. If they decided not to switch, then they would earn £1 if the set-aside card was a heart card, and if they switched to a club card, then they would get £1 if the set-aside card was a club card.

Because it was common knowledge that the revealed card was always a losing card, switching was the optimal solution for a utility maximizing decision maker. By switching, one increases the chance of winning from 1/3 (the probability of being endowed with the correct card initially) to 2/3. This is the case because the two cards that were not set aside have a combined probability of 2/3 of containing the winning card. However, because one of these two cards is always revealed, the probability of the winning card—when switching—is 2/3 (but remains at 1/3 when not converting).

Typically, switching rates for individuals are fairly low (around 30%; Friedman 1998). The generally low switching rates have been attributed mostly to people's tendency to assign equal probabilities to all possible outcomes in a set (Fox and Levav 2004) and to status-quo bias (Samuelson and Zeckhauser 1988). Slembeck and Tyran (2004) showed that groups switch more often than individuals, particularly when they compete against other groups. Yet, Slembeck and Tyran (2004) did not examine any transfer of knowledge from groups to subsequent individual decision-making.

3.3. The Wason Selection Task

The task was originally designed to test whether individuals employ the rules of formal logic, when testing conditional statements of the form "if p, then q" (Wason 1966). In the standard problem, individuals are shown four cards. The cards have a letter on one side and a number on the other side. The participants' task is to verify the conditional rule "if there is a vowel (the p card) on one side, then there is an even number (the q card) on the other side" by identifying the minimal set of cards that must be flipped to fully test whether the rule is true or false. The cards shown are E (p), K (not p), 2 (q), and 7 (not q). Formal logic analysis requires checking (a) the truthful implication of the rule by flipping the card E (p) and (b) the potential falsification of the rule by flipping the card 7 (not q).

Typically, only approximately 10% to 20% of the participants solve the problem correctly (Griggs and Cox 1983). Around one-third of the participants select only card E (p) and about one-half of the participants select the incorrect combination of cards E (p) and 2 (q) (see Evans and Over 2004 for a review). These findings have been replicated in numerous studies (Evans and Over 1996), with recent evidence suggesting that the task is not only popular, but also a suitable tool for measuring actual reasoning ability (Evans and Ball 2010).

4. Study 1: Are Teams More Strategic Than Individuals, and Is Exposure to Team Decision Making Beneficial for Long-Term Knowledge Transfer?

4.1. Participants

One hundred and twenty students (40% male) from Imperial College London, aged 18 to 31 years (mean = 21.68, SD = 2.58), participated in the study. Sessions lasted approximately 110 minutes, and participants earned, on average, £22.48 ($35.54; SDs = £4.80/$7.59).

4.2. Experimental Design and Procedure

We contrasted learning, and subsequent knowledge transfer, in 10 markets consisting of four individual traders each ($n = 40$) and 10 markets with four two-person teams ($n = 80$) each. We refer to the two conditions as *INDIVIDUAL* and *TEAM*, respectively.

In Stage I, all participants were asked to solve the Monty Hall problem individually (see Problem 1 in Table A1 of the online appendix, available at http://homepage.uibk.ac.at/~c40421/pdfs/MS-12-01011_R1_Supplementary_Appendix.pdf). If the set-aside card corresponded to the card that participants held (either from endowment or by conversion), they earned £1 (and £0 otherwise), but payment was received only after Stage III.

In Stage II, participants were assigned to the experimental conditions (INDIVIDUAL or TEAM). We ensured that each market (consisting of either four individuals or four two-person teams) had exactly one person who decided to switch in Stage I.[2] The remaining positions were filled by randomly sampling participants who decided not to switch in Stage I. This procedure ensured that markets were as similar as possible in terms of their composition in the INDIVIDUAL and TEAM conditions. Because

[1] Note that a player does not trade his club card with the still unrevealed card. The latter remains unrevealed, and there is also the unrevealed set-aside card. Switching cards means that the trader can switch from his suit to the other suit that has not been revealed.

[2] Among the four individual traders, exactly one trader switched in Stage I, and, similarly, among the four two-person teams, exactly one member of one team switched in Stage I.

of our insistence to have exactly one participant who switched in Stage I in each market, not all individuals who completed Stage I participated in Stage II. Some were invited to participate in unrelated consumer surveys and others were paid and excused.

The markets were computerized (implemented with the software *z*-Tree; Fischbacher 2007) and were based on the study by Kluger and Wyatt (2004). Trading started only when participants had solved correctly all the items of a short quiz, designed to check understanding of the instructions. Markets consisted of 10 trading periods. At the beginning of each period, participants were shown three cards (clubs, diamonds, hearts). These cards were shown facedown on the computer screen, shuffled, and one card was randomly selected to be the set-aside card. Participants were endowed with three cards of one type (clubs, diamonds, or hearts). The same procedure was applied to all markets and periods, but the cards selected varied across periods.

Participants/teams were endowed with 300 experimental currency units (ECUs) at the beginning of each period (with an exchange rate of 100 ECUs = £1) and three cards of a given suit. Participants then traded their cards in a continuous double auction for 90 seconds.[3] Afterward, a losing card was revealed on the screen. Participants were endowed with 300 additional ECUs and three additional cards of the initial type, and had the chance to trade their card holdings for another 90 seconds in a continuous double auction.[4] Participants could only trade the newly endowed cards, and all started with 300 ECUs at the start of this second auction (to ensure symmetry across subjects). At the end of a period, participants' earnings amounted to the sum of their cash holdings in the two auctions and the total number of cards held at the end of each of the two auctions. Finally, participants had the option to convert all, none, or some of their cards. They were promised 100 ECUs for each card held (either through trading or conversion) that matched the set-aside card. Finally, all cards were revealed, participants received feedback about their payoffs in that period, and the next period started. At the conclusion of the market, one period was chosen at random, and participants received the payoff from that period (i.e., cash holdings plus card earnings). Payments were received after Stage III.

In Stage III, participants were shown seven new Monty Hall problems with three to five cards each (see Table A1 of the online appendix), allowing us to test for potential knowledge transfers. One of these problems was chosen at random and formed the basis of the participants' payoffs for this stage. Participants received payments for Stages I–III.

Stage IV took place five weeks after the experiment was completed. We emailed to all the participants the same questionnaire (seven Monty Hall problems) used in Stage III and asked them to email us their decisions. Over 80% of the participants responded. Again, one of the seven problems was chosen at random to determine participants' payoffs. Payments could be collected in person from the lead author.

4.3. Results

4.3.1. Stage I. A total of 16.67% of the participants decided to switch and 83.33% did not. This information was used to create markets in Stage II with exactly one person who switched in Stage I.

4.3.2. Stage II. We averaged the trading prices across auction blocks of five periods (block 1, periods 1–5; block 2, periods 6–10) and subjected them to a three-way mixed analysis of variance (ANOVA) with the between-subjects factor *decision unit* (INDIVIDUAL versus TEAM) and the within-subjects factors *auction type* (before card revelation versus after card revelation) and *trading block* (1 versus 2). The results show a significant main effect for decision unit ($F(1, 18) = 63.58$, $p < 0.05$, $\eta^2 = 0.78$). The rational pricing level of the cards is approximately 67 ECUs, i.e., two-thirds of the 100 ECUs prize (Kluger and Wyatt 2004).[5] Figure 1 shows that teams are much closer to this pricing level than individuals. On average, teams bid 61.89 ECUs (SD = 11.90), whereas individuals bid 107.37 ECUs (SD = 13.56). We also found significant interactions for auction type by trading block ($F(1, 18) = 7.99$, $p < 0.05$, $\eta^2 = 0.31$) and decision

[3] Trading requires participants to explicitly value the cards and, potentially, infer their values from the behavior of the other market participants (e.g., from the submitted bids, asks, and trading prices). This helps learning about the probabilities with which cards make money. For instance, declining prices reveal the market's perception that a card earns its holder money with a lower probability. Trading also offers participants an opportunity to make some additional money by selling cards at a higher price than their original purchase price. Thus, individuals may wish to trade (1) to receive payments if their cards matched the set-aside card (see details below) and/or (2) to make money from selling cards at prices exceeding the initial purchase prices.

[4] We had two separate double auctions (one before the losing card was revealed and one after the losing card was revealed) to get a sense of how participants' valuations of the cards changed as a function of how many cards there were. Prior research suggests that people assign equal probabilities across as many unknowns as are present (Fox and Levav 2004). For the Monty Hall task, this suggests that most people believe the probability of winning is 1/3 before the losing card is revealed and 1/2 after the losing card is revealed. Having two separate auctions (one before and one after the losing card was revealed) allows us to infer these probabilities from the average trading prices in these two auctions.

[5] Any card that is acquired through trading can be converted ultimately (thus changing suits). The converted card has a 2/3 probability of winning, meaning that it pays in expectation 100 ECUs $*$ $2/3 \approx 67$ ECUs. Hence, the rational price for any card should match this expected yield from the card that will ultimately be in a player's possession (i.e., the converted card).

Figure 1 Average Trading Prices Across Auction Periods and Types by Teams and Individuals (Study 1)

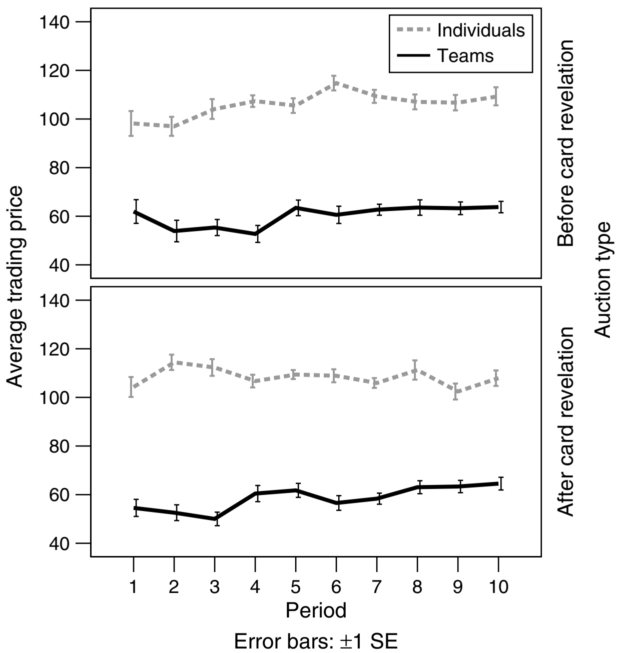
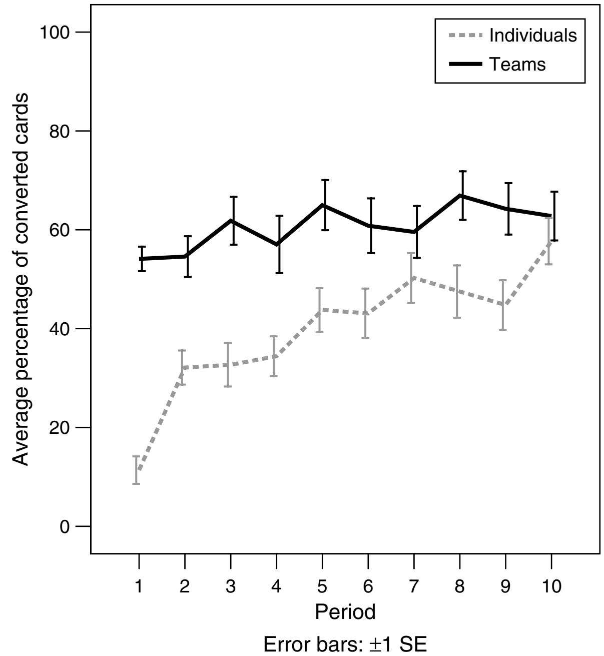


Figure 2 Average Percentages of Converted Cards Across Periods by Teams and Individuals (Study 1)



unit by auction type by trading block ($F(1,18) = 6.13$, $p < 0.05$, $\eta^2 = 0.25$). In the TEAM condition, we observed moderate drops in average trading prices after card revelation in both trading blocks (from 61.30 to 59.62 ECUs in block 1, and from 64.44 to 62.19 ECUs in block 2). For the INDIVIDUAL condition, in contrast, we observed an increase in average trading prices after card revelation in block 1 (from 106.00 to 111.86 ECUs) and a decrease in block 2 (from 107.13 to 104.51 ECUs).

At the end of each trading period, participants had the option to convert (all, none, or some) of their cards. Converting all their assets would be a perfectly rational solution to the problem. However, partial conversion of some cards may be considered hedging by mixing one's assets to cover several bases at once. Besides, converting only some of their cards would provide valuable information to participants. By doing so, participants had the opportunity to identify the correct solution by tracking—across periods—whether converting yields, on average, a higher or a lower winning probability. The results of a two-way mixed ANOVA with the average percentage of conversions as the dependent variable and the between-subjects factor *decision unit* (INDIVIDUAL versus TEAM) and within-subjects factor *trading block* (1 versus 2) reveal significant main effects for decision unit ($F(1,18) = 38.41$, $p < 0.05$, $\eta^2 = 0.68$) and trading block ($F(1,18) = 35.41$, $p < 0.05$, $\eta^2 = 0.66$), as well as a significant interaction effect for decision unit by trading block ($F(1,18) = 11.80$, $p < 0.05$, $\eta^2 = 0.40$). The unit of analysis is the INDIVIDUAL or TEAM. Figure 2 shows the percentage of conversion rates across periods. Clearly, the teams start out more strategically than individuals by converting a higher proportion of their card holdings early on. This can be inferred from the near 50% conversion rate in the first period (see Figure 2). Individuals, in contrast, tend to start out by rejecting the conversion option, but convert their cards at an increasing rate later on. For instance, in the very first period, 62.5% of the individuals converted none of their cards, whereas all teams converted at least one of their respective cards. This finding highlights that teams used a hedging strategy (i.e., converted at least some of their cards) earlier than individuals.

4.3.3. Stage III. Participants who were part of teams in Stage II converted cards at a significantly higher rate than those participants who traded individually. On average, former team members converted 4.24 cards (SD $= 1.82$), whereas individuals converted 3.35 cards (SD $= 1.90$, $t(118) = 2.48$, $p < 0.05$).

4.3.4. Stage IV. Five weeks after the experiment participants were asked to complete the seven Monty Hall problems again. The response rate was 80% for the teams and 82.5% for the individuals. On average, former team members converted 4.28 cards (SD $= 1.57$), whereas individuals converted 3.58 cards (SD $= 1.46$, $t(95) = 2.15$, $p < 0.05$). We next performed a two-way mixed ANOVA with conversion rate as the dependent variable and the between-subjects factor *decision unit* (INDIVIDUAL versus TEAM) and the within-subjects factor *days after trading* (0 versus

35 days). The results reveal a significant main effect for decision unit ($F(1, 95) = 5.37$, $p < 0.05$, $\eta^2 = 0.05$), with former team members showing a significantly higher conversion rate than subjects who participated in the INDIVIDUAL markets. We did neither find a significant effect for timing (days after trading) nor an interaction effect. This suggests that knowledge transfers from team decisions to individual decisions persist.

4.3.5. Transfer Analysis Across Stages. We averaged the individual conversion rates across Stages III and IV for each distinct class of card problems (three-, four-, and five-card problems; see Table A1 of the online appendix for a list of the problems used). On average, former team members converted in 60.31% (SD = 32.34) of the four-card problems and in 60.63% (SD = 28.81) of the five-card problems, whereas the corresponding percentages for individuals were 46.25% (28.05) and 46.67% (26.47), respectively. Former team members performed significantly better than the participants in the individual markets for these two problems. This finding suggests that team decision making is particularly effective for new problems, as four- and five-card problems of the task were not used in the initial market experiment.

4.4. Discussion

Study 1 demonstrates that teams outperform individuals and that this advantage is preserved even five weeks after the original interaction took place. Importantly, the pricing of the cards suggests that the advantage of teams was evident even before trading took place. Teams priced cards closer to the optimal level from the very first period, suggesting that teams analyzed and solved the problem more efficiently than individuals. In the second study, we investigated how teams *improve* their problem-solving skills by using a pure logic problem (rather than a problem of Bayesian updating, as in Study 1). This allowed us to check the robustness of the results obtained in Study 1 for different problems and to observe more directly how the advantage of team decision making materializes. For this purpose, we used the Wason selection task. In Study 2, we videotaped the teams' discussions in an effort to shed more detailed light on the underlying decision processes than was possible in Study 1.

5. Study 2: Do Teams Learn Faster Than Individuals and Are They More Successful in Transfering Knowledge?

5.1. Study 2a

5.1.1. Participants. One hundred and twenty undergraduate students (42.5% male) from the University of Jena, aged 19 to 36 years (mean = 23.24, SD = 2.92), participated in the study. The recruitment of the participants was done with the Online Recruitment System for Economic Experiments (ORSEE; Greiner 2004). Sessions lasted approximately 120 minutes, and participants earned, on average, €8.06 ($10.88; SDs = €3.67/$4.95).

5.1.2. Experimental Design and Procedure. In Stage I, participants were asked to solve one Wason selection task individually (see first problem of Table A2 in the online appendix). Correct choices were rewarded with €4 ($5.40), but feedback and payments were delayed to the end of the experimental session.

In Stage II, 40 participants were randomly assigned to groups of four in the INDIVIDUAL condition and 80 participants to groups of eight in the TEAM condition. In the latter, participants were then randomly split into four two-person teams and were given time to discuss the problem prior to market opening.

Participants were told that each card has a color on one side and a geometric figure on the other side. Participants were instructed to test the rule "If the card is red (p) on one side, then there is a triangle (q) on the other side" (see Table A2). The four cards shown in the instructions were red (p), black (not p), triangle (q), and rectangle (not q). For the remainder of the paper, we refer to the p card as Card I, the non-p card as Card II, the q card as Card III, and the non-q card as Card IV. This implies flipping Cards I and IV is the correct solution.

We used a continuous combinatorial auction, allowing participants to submit buying offers (bids) for each of the 15 possible card combinations (see Figure A1 in the online appendix for a schematic screenshot of the auction and a complete listing of the card combinations) at any time during an auction period. Overall, experimental sessions consisted of 30 auction periods with 60 seconds each. Individuals/teams were randomly assigned the role of participant/team A, B, C, or D. The same Wason selection problem (described above) was used in each period.

At the beginning of each period, participants were endowed with 500 ECUs that were equivalent to €5 ($6.75 at the time of the study). A total of 16 cards (four Card Is, four Card IIs, four Card IIIs, and four Card IVs) were auctioned in each period. During each period, participants could submit bids for any card combination, as long as they had enough cash holdings. All bidders could see the other participants' bids after they were submitted. At the end of each period, the winners of the auction were determined by a computer program implementing an algorithm designed to maximize the auctioneer's (experimenter's) revenue (i.e., the bids before paying dividends). The algorithm used an exhaustive enumeration of card partitions (for a discussion of a similar problem, see Sandholm 2002, Pekeč and Rothkopf 2003).

After each period, participants (teams or individuals) were awarded dividends of 200 ECUs (€2) per correct pair of cards (I and IV), regardless of which other cards they held. Teams' payoffs were doubled and split equally between the two members. Dividends were paid out at the end of the experiment and, hence, could not be used to increase one's cash endowment of subsequent periods. Participants were not allowed to convert their ECU holdings (that were not used for bidding) to actual cash at the end of the experiment. This restriction was designed to induce participants to acquire cards, rather than save up their cash holdings. We did not allow participants to buy cards on credit. Payoff feedback about dividend earnings was provided privately to individual participants and teams after each period.

We expect that learning in the auction is due to the participants' ability to track their own behavior and the behavior of the other participants (easily identified by unique labels, A, B, C, and D). The other bidders' bids are informative of their valuation of different (sets of) cards, from which a bidder might infer what is most likely the correct card combination. Own behavior is important for learning because payoff feedback between periods allows inferring, in an optimal case, the correct solution, and, in other cases, whether a particular bundle of cards is more or less likely to be the right card combination.

In Stage III, participants were asked to solve eight Wason problems individually (for a complete listing, see Table A2 in the online appendix). The location of the solution cards was varied across the problems (meaning that in some problems the solution was to flip Cards I and IV, and in others to flip Cards II and IV, I and III, etc.). This task tests for *general knowledge transfers*, because participants need to fully understand the solution of the problem to consistently identify the correct card combinations.

At the conclusion of a session, participants were paid their combined earnings from Stage I, three periods from Stage II (one randomly drawn auction from each block of 10 auctions: 1–10, 11–20, 21–30), and one randomly chosen problem from Stage III. In addition, individuals received €2.50 ($3.38) for showing up. Participants in the TEAM condition received a show-up fee of €4.00 ($5.40).[6]

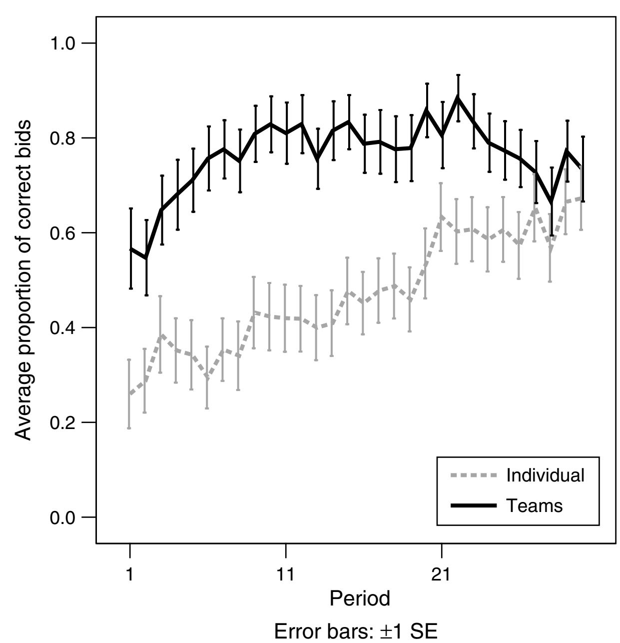
5.1.3. Results. *Stage* I. The average rate of correct solutions was 20.0%. The solution rates of subjects who were subsequently assigned to the INDIVIDUAL and TEAM conditions were 22.5% and 18.75%, respectively, and did not differ significantly.

Stage II. We computed the proportion of bids on the correct solution out of the total amount of submitted bids for each individual/team in each auction period. Bids on the correct solution were defined as bids for the combination of Cards I and IV, as well as bids for those two individual cards, when placed at the same time and for the same number of cards. Note that our definition is conservative and represents a lower bound of the target quantity. Although participants received dividends for card combinations that included redundant cards in addition to the solution (e.g., I, II, and IV), our definition requires participants to identify the solution cards precisely.

Because bidding in the auction is a function of all the bidders in a group, the unit of statistical analysis is the auction rather than the individual bidder or team. The proportion of bids on the correct solution was aggregated across the four individuals/teams in each auction. Figure 3 shows the proportion of bids that was placed on the correct solution as a function of experimental condition and period. We observe a monotonic increase of bids on the correct solution across auctions for both individuals and teams, suggesting that participants learn the correct solution.

We averaged the bids across auction blocks of five periods (block 1, periods 1–5; block 2, periods 6–10; ...; block 6, periods 26–30) and subjected them to a two-way mixed ANOVA with the between-subjects factor *decision unit* (INDIVIDUAL versus TEAM) and the within-subjects factor *auction block* (1–6). The results show significant main effects for decision unit ($F(1, 18) = 5.64$, $p < 0.05$, $\eta^2 = 0.24$). In fact, teams bid, on average, in 76% of the cases for the correct solution, whereas individuals do so in only 51% of the cases. Auction block is also significant ($F(5, 14) = 6.16$,

Figure 3 **Average Proportion of Bids on the Correct Solution (and Standard Errors) in the Individual Condition and the Team Condition Across Auction Periods (Study 2a)**



[6] The difference in show-up fees reflects the fact that the laboratory for team decisions was located further away from the university.

$p < 0.05$, $\eta^2 = 0.69$), indicating learning, but there is no interaction effect with the decision unit.

Stage III. Overall, subjects solved 56.7% of the tasks correctly, which is significantly higher than the solution rate in Stage I (Wilcoxon signed ranks test, $z = 8.16$, $p < 0.05$). To isolate the net learning effect, we consider only those participants who did not solve the Wason task correctly in Stage I. We compared the corresponding solution rates of those participants who bid individually with those who bid as part of teams in Stage II (where no team member had solved the task in Stage I). Solution rates do not differ significantly between these groups ($z = 1.03$, $p > 0.05$ by a Mann–Whitney test), suggesting that there was no advantage to individuals bidding in teams (mean = 51.5%) over bidding alone (mean = 42.7%) in terms of knowledge transfer.

5.1.4. Discussion. Study 2a demonstrates that in the context of combinatorial auctions considerable learning takes place and it is transferred successfully to postauction behavior. Confirming our main hypothesis, we found that teams learned the solution to the Wason selection task faster than individuals, but members of teams were not necessarily more successful in transferring their knowledge to a set of new reasoning problems in Stage III. Figure 3 suggests that this might be due to the length of bidding: The learning advantage of teams over individuals, evinced by the proportion of bids on the correct cards, diminishes across the 30 auction periods. This means that at the beginning of Stage III subjects from both the INDIVIDUAL and the TEAM conditions achieve similar levels of learning. As a consequence, we do not observe differences in the overall transfer of knowledge (across all sessions).

To test this explanation, we investigate next whether teams are superior to individuals in terms of transferring their knowledge to new problems when the learning phase is much shorter—10 auctions instead of 30.

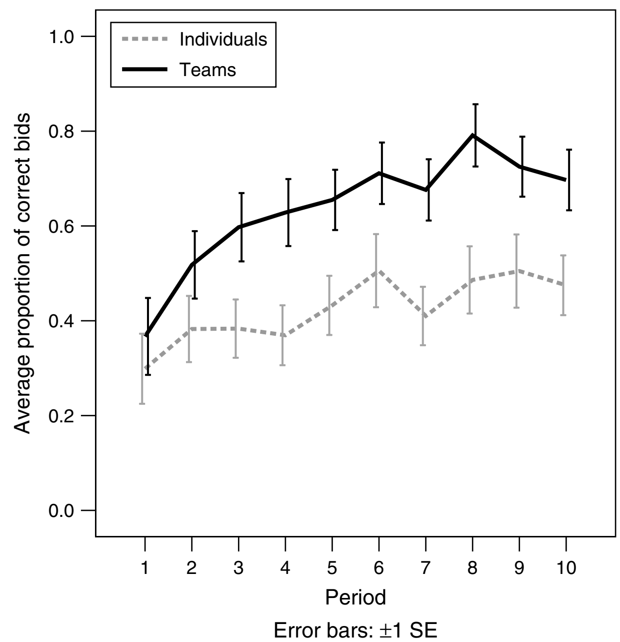
5.2. Study 2b

5.2.1. Participants. One hundred and twenty undergraduate students (45% male) from the University of Jena, aged 18 to 34 years (mean = 22.56, SD = 2.82), participated in the study. None of them had participated in Study 2a. Recruitment was done with ORSEE (Greiner 2004). Sessions lasted approximately 95 minutes, and participants earned, on average, €6.75 ($9.11; SDs = €3.17/$4.28).

5.2.2. Experimental Design and Procedure. Study 2b is an exact replication of Study 2a with two changes: We reduced the number of auction periods from 30 to 10, and we determined payoffs for Stage II by randomly selecting only 1 of the 10 periods.

5.2.3. Results. *Stage* I. The average rate of correct solutions was 28.3%. The solution rates of subjects who were subsequently assigned to the INDIVIDUAL and TEAM conditions were 27.5% and 28.75%, and did not differ significantly.

Figure 4 Average Proportion of Bids on the Correct Solution (and Standard Errors) in the Individual Condition and the Team Condition Across Auction Periods (Study 2b)



Stage II. Figure 4 shows the proportion of bids on the correct solution across periods as a function of experimental condition. We analyzed the proportion of bids on the correct solution in a two-way mixed ANOVA with the between-subjects factor *decision unit* (INDIVIDUAL versus TEAM) and the within-subjects factor *auction block* (periods 1–5 versus periods 6–10). The results replicate those in Study 2a and show significant main effects for decision unit ($F(1, 18) = 4.54$, $p < 0.05$, $\eta^2 = 0.20$) and auction block ($F(1, 18) = 10.55$, $p < 0.05$, $\eta^2 = 0.37$), but no interaction effect. In fact, teams bid, on average, in 65% of the cases for the correct solution, whereas individuals do so in only 45% of the cases. Overall, correct bids increased, on average, from block 1 to block 2 from 49% to 61%.

Stage III. Overall, participants solved 57.0% of the transfer problems, which is again significantly better than the solution rates in Stage I (Wilcoxon signed ranks test, $z = 5.28$, $p < 0.05$). We compared the solution rates of those participants who failed to solve the Wason task in Stage I and bid individually or as part of a team in Stage II (where no team member had solved the task in Stage I). Individual who participated as part of teams solved a significantly higher percentage of transfer problems (56.4%) than individuals who participated in individual auctions (27.6%; Mann–Whitney test, $z = 2.76$, $p < 0.05$).

5.2.4. Discussion. Study 2b replicates all the results of Study 2a regarding the superior learning of teams and demonstrates that individuals who bid as part of a team were more successful in transferring their acquired knowledge to a set of new Wason problems than the individual bidders when the learning period was relatively short.

6. Study 3: Can Teams Learn with Less Specific Feedback Than Individuals?

In Study 3 we expose our previous findings to an important stress test. We examine whether teams can achieve similar results with weaker and less specific performance feedback and whether knowledge transfer is still better under such less favorable conditions. This stress test would lend higher credibility and broader relevance to our claims by showing that the beneficial knowledge transfer from teams to subsequent individual decisions is not restricted to specific information and feedback conditions (such as those used in Studies 2a and 2b). Therefore, we use a different market mechanism—a continuous double auction—in which learning is more difficult than in the combinatorial auctions. We also manipulate the quality of earnings' feedback. The distinctive characteristics of the double auction markets that make learning more difficult are as follows:

—The market is "thin" (only four traders per auction), which leads to noisy trading prices.

—Individual traders cannot be identified and imitated. Only aggregate (and anonymous) market behavior is observed.

—The traders' motivation is ambiguous because this mechanism provides an incentive to acquire incorrect cards, as long as traders believe that other participants may wish to buy these cards later at a premium.

—Cards are traded individually. Because the solution requires traders to hold two cards to receive dividends, they expose themselves to execution risk (holding one card by itself is worthless without having the other).

Based on our previous findings, we hypothesize that teams would achieve higher levels of learning and would be more successful at transferring their knowledge than individuals, despite the noisy market mechanism.

6.1. Participants

Two hundred and forty undergraduate students (41.67% male) from the University of London, aged 19 to 36 years (mean = 22.92, SD = 2.68), participated in the study. Sessions lasted approximately 100 minutes, and participants earned, on average, £13.34 ($19.89; SDs = £4.58/$6.83).

6.2. Experimental Design and Procedure

We contrasted learning, and subsequent knowledge transfers, in a two-by-two between-subjects design. The two factors were the decision unit (INDIVIDUAL versus TEAM) and the performance feedback (strong versus weak). We ran 10 markets in each of the four cells, with $n = 40$ participants in each of the two individual conditions and 40 dyads ($n = 80$) in each of the two team conditions.

In Stage I, participants were asked to solve the Wason selection task (first problem of Table A2 in the online appendix) individually. Correct choices were rewarded with £2 ($2.98), but feedback and payoffs were delayed to the end of the experimental session.

In Stage II, participants were randomly assigned to one of the four experimental conditions of trading in computerized double auctions (implemented with the software *z*-Tree; Fischbacher 2007). Each market consisted of 12 trading periods during which participants could buy or sell the four cards of another Wason selection task (second problem in Table A2) in continuous anonymous double auctions (see Figure A2 in the online appendix for a schematic screenshot of the auction). Each market consisted of four traders (who were, depending on the condition, individuals or two-person teams).[7]

At the beginning of each period, participants were endowed with 120 ECUs (exchange rate: 100 ECUs = £10) and with four cards of the same type (i.e., Card I, Card II, Card III, or Card IV). To induce trading, only one trader (individual participant or dyad) in each market was endowed with a given card. The card assignment was determined randomly in each period. Trading periods lasted for 180 seconds. Participants could submit bids and asks; they could also accept standing offers (bids and asks) by other market participants. Only improving offers, i.e., higher bids and lower asks, were allowed. Participants were shown lists of concluded contracts for each card (in chronological order) and were informed about the remaining trading time and the current period number. Participants were not granted any credit and were not allowed to sell cards short; i.e., they were only allowed to make bids up to their cash holdings and submit asks for cards they actually owned.

If participants held the correct cards at the end of an auction period, they received dividends of 80 ECUs (£8) for each complete set of solution cards. We varied the quality of the performance feedback that participants received at the end of each trading period

[7] In the TEAM condition, communication between team members was verbal. Team members sat next to each other in front of their PC terminal and discussed their strategy and actions before and during the auction periods. Participants were instructed to keep their voices low to not reveal their trading strategies to the other participants. Teams were given the same amount of time as individuals. So, teams needed to be quick and were potentially exposed to more time pressure than individuals—something that would make the superior performance of teams even more remarkable.

(see Figure A3 in the online appendix for a schematic screenshot of the information provided). Participants in the *strong*-performance feedback condition were informed about the dividends associated with each of the four cards separately. In this condition it was made explicit that Cards II and III earned no dividends, and that Cards I and IV would earn 40 each *if* held in pairs (see Figure A3a). In contrast, participants in the *weak*-performance feedback condition were only shown the aggregate amount of dividends, without a direct link to the individual card holdings (see Figure A3b), so in most cases a trader could not directly infer which card(s) paid dividends. At the end of the experimental session, one period was randomly selected, and participants obtained their cash holdings and dividend payments for that particular period.

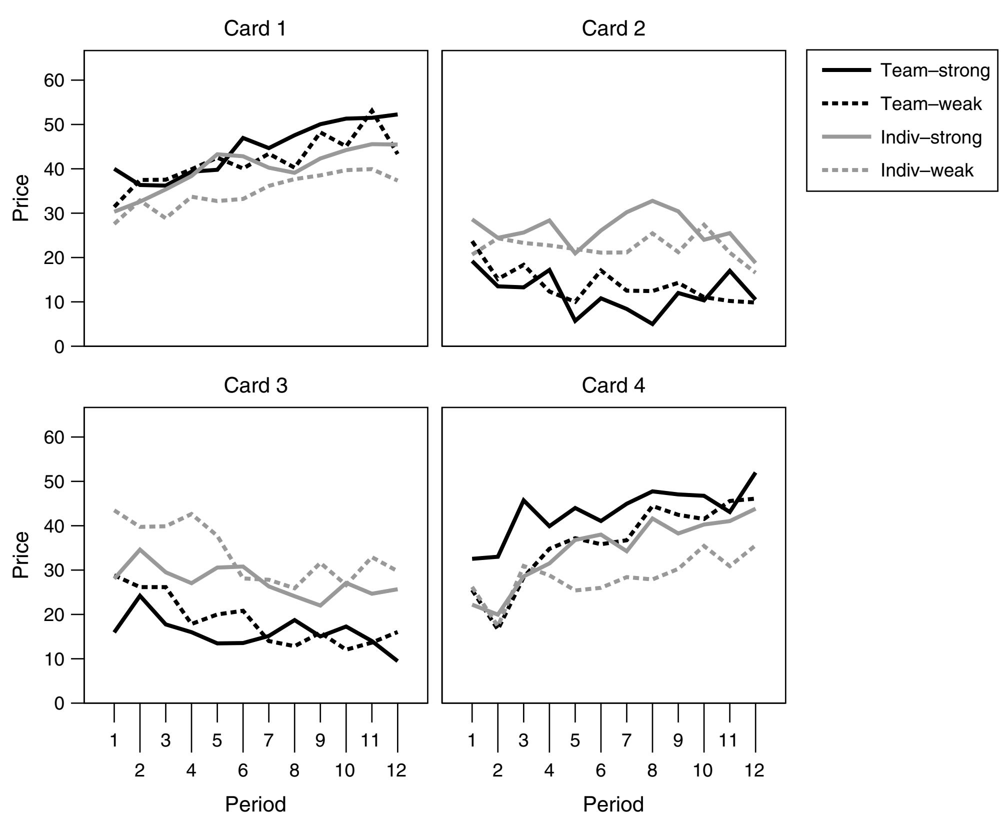
In Stage III, participants were asked to solve eight new Wason problems (identical to Studies 2a and 2b) individually. One of the eight problems was randomly selected, and participants received £2 if they solved it correctly, on top of their earnings from Stages I and II. If participants' total earnings fell short of £4 ($5.96), they received this amount.

6.3. Results

6.3.1. Stage I. The average solution rate was 7.9%. There was no significant difference between subjects who were later assigned to the INDIVIDUAL (8.8%) and TEAM conditions (7.5%).

6.3.2. Stage II. Figure 5 shows the average trading prices for the four cards across periods as a function of decision unit and feedback. Prices for correct (incorrect) cards were generally higher (lower) for TEAM (INDIVIDUAL) traders and with strong (weak) performance feedback. To confirm these impressions, we aggregated the trading prices across periods for each of the four cards as a function of experimental condition and the 10 markets. We then computed the average trading price for the correct cards and subtracted the average trading price for the incorrect cards. This measure was subjected to a two-way ANOVA with the between-subjects factors decision unit (INDIVIDUAL versus TEAM) and performance feedback (strong versus weak). The results showed significant main effects for decision unit ($F(1, 35) = 87.56, p < 0.05, \eta^2 = 0.71$). The mean difference between the trading prices for correct cards and incorrect cards was 27.12 (SD = 6.96) for teams, but only 8.36 (SD = 6.97) for individuals. The effect of feedback was also significant ($F(1, 35) = 9.09, p < 0.05, \eta^2 = 0.21$). With strong feedback, the difference in trading prices was 20.73 (SD = 12.09), and with weak feedback it was only 15.09 (SD = 10.90). There was no interaction effect of decision unit and feedback.

Figure 5 Average Trading Prices for the Four Cards as a Function of Experimental Condition and Period (Study 3)



Note. Lines show mean.

6.3.3. Stage III. Overall, participants solved 42.71% of the transfer problems, which was significantly better than the solution rates in Stage I (Wilcoxon signed rank test, $z = 9.06$, $p < 0.05$). To isolate the learning effect, we focused only on those participants who did not solve the Wason task correctly in Stage I. We compared the corresponding solution rates of those participants who traded individually with those who traded as part of teams (where none of the team members solved the task in Stage I). Individuals, who traded as part of teams solved a significantly higher percentage of transfer problems (43.7%) than individuals who traded as individuals (27.2%) (Mann–Whitney test, $z = 2.25$, $p < 0.05$).

We also computed for each individual the fraction of correct choices across the eight transfer problems and subjected this measure to a two-way ANOVA with the between-subjects factors decision unit (INDIVIDUAL versus TEAM) and performance feedback (strong versus weak). We found a significant main effect for decision unit ($F(1, 236) = 5.90$, $p < 0.05$, $\eta^2 = 0.02$). Former team members answered, on average, 3.83 problems correctly (SD = 3.83) in Stage III, but individuals solved only 2.59 (SD = 3.55). There was neither a significant effect for performance feedback nor an interaction effect in the ANOVA.

6.4. Discussion

Study 3 shows that teams were able to learn the correct solution to the Wason selection problem better than individuals even in competitive markets with less specific feedback. In particular, it is noteworthy that the panels pertaining to the cards that make up the correct solution in Figure 5 show that the trading prices of *teams with weak feedback* are indistinguishable from the prices of *individuals with strong feedback*. This implies that team decision making can compensate for worse feedback. Like in Study 2b, members of teams were also more successful in transferring their acquired knowledge to new problems in Stage III of our Study 3. This shows that the result from Study 2b is not dependent on the type of feedback given.

7. Synopsis: What Accounts for the Superior Learning in Teams and the Better Transfer to Individual Decisions?

7.1. Do Teams Start Off with Superior Information?

In Study 1, we controlled for the strength of the available information by ensuring that exactly one participant in each market knew the correct solution. However, for the two other studies, one possibility for the superior performance of teams might have been that they started off with better information compared to the individuals. Although in total there were more subjects in the TEAM condition (50) who solved the problem correctly in Stage I than in the INDIVIDUAL condition (27), in the aggregate the level of information (i.e., the total number of correct premarket solutions across all the players (4 or 8) in a given market) is not superior in the larger markets (TEAM) (Kolmogorov–Smirnov test, $D = 0.20$, $Z(D) = 0.89$, $p > 0.05$), so we reject this account.

7.2. Truth Wins and Team Performance

Another explanation of our findings would be that teams perform at the level of their best members. According to such a "truth wins" norm, a knowledgeable minority of group members can convince the majority by demonstrating the correct solution (Laughlin 1980). This effect would shift the level of learning and knowledge transfers upward in teams (relative to individuals). To test this explanation we compared the proportion of bids on the correct solutions of the *best individual* in each market (aggregated across all periods in Studies 2a and 2b) and the *average team* in each market (aggregated across periods). We did not find statistically significant differences between these distributions in Studies 2a and 2b, suggesting that the average team performs as well as the best individual, but not better.

However, a similar analysis for Study 3 shows that the average team performed significantly better than the best individual traders. This analysis is based on the comparison of the bids submitted for Cards III and IV.[8] We calculated for each individual/team the difference in bids submitted for Cards IV and III, aggregated this measure across periods and compared the *best individuals* (the one with the highest difference between the bids submitted for Cards IV and III) to the *average team* in each market as a function of performance feedback. The results show significant main effects for decision unit (teams outperform individuals: $F(1, 36) = 7.59$, $p < 0.05$, $\eta^2 = 0.17$) and performance feedback (there is an advantage for strong feedback: $F(1, 36) = 5.90$, $p < 0.05$, $\eta^2 = 0.14$), but no interaction effect. Table 1 shows the mean differences between bids for Cards IV and III.

Finally, we compare team and individual performance on markets where none of the participants solved correctly the Wason problem individually in Stage I. There were a total of 24 such markets in Study 3 (10 in the TEAM condition and 14 in the

[8] All our prior analyses suggest that the crucial indication of identifying the correct solution in the Wason selection task hinges on the insight that Card IV is essential to test it, although the incorrect Card III seems the initially most likely candidate for a majority of subjects. For instance, in Stage I, 47% of the participants picked Cards I and III, whereas only 7.9% picked Cards I and IV.

Table 1 Mean Difference Between Bids Submitted for Cards IV and III as a Function of Decision Unit and Performance Feedback (Study 3)

	Performance feedback	
	Weak	Strong
Decision unit	Mean (SD)	Mean (SD)
Best individual	10.51 (19.07)	18.05 (8.87)
Average team	19.28 (9.19)	29.98 (6.14)

INDIVIDUAL condition). We ran the same ANOVA of the difference in bids for Cards IV and III on this restricted sample and obtained similar significant effects for decision unit ($F(1,20) = 28.94$, $p < 0.05$, $\eta^2 = 0.59$) and feedback ($F(1,20) = 6.25$, $p < 0.05$, $\eta^2 = 0.24$), confirming that teams do better than individuals and strong feedback is more effective than weak feedback.

These results provide evidence that teams can perform better than the best individual traders! A reasonable explanation is that, as part of their interaction, team members challenge each other's solutions, thereby inducing deeper and more critical levels of thinking and analysis, which help in identifying the correct solution (Moshman and Geil 1998). To investigate further this explanation, we analyze the content of the team interactions.

7.3. A Content Analysis of the Team Interactions

We analyzed the video transcripts of the 40 teams of Study 2a.[9] We classified the participants' strategies, as inferred from their verbal interactions, into eight distinct classes.[10] Table 2 summarizes our content analysis. The categories are listed in the order of their prevalence and broken by the stage of the experiment. Clearly, most of the interactions took place in the first third (periods 0–10) of the study, and their frequency declined from that point on. This observation is consistent with the finding that, on average, performance stabilizes and plateaus at that stage.

Table 2 shows two distinct patterns. On the one hand, teams tried to infer the correct solution by imitating the behavior of others (strategy 1), which accounted for over 29% of all verbalized strategies. On the other hand, a substantial number of teams (44%) engaged in more strategic attempts to infer the correct solution. These teams put themselves in the position of their opponents (strategy 2), tried to infer the solution from the bids that were submitted for the various card combinations (strategy 3), and tried to strategically eliminate incorrect card combinations by varying their bids across periods (strategy 4).

There is also some, but much less, evidence for the demonstrability of the correct solution (strategy 5), and seeking to discuss confirmatory (strategy 6) rather than disconfirming evidence (strategy 7). In some teams group consensus was found by allowing individual members to alternate between their preferred solutions (strategy 8).

Of course, these data are only available for the teams. We cannot rule out the possibility that individuals consider similar strategies. However, even if they do, evidently they cannot implement them as efficiently and successfully as the teams. We speculate that the dyads' advantage is due to their ability to share, test, validate, and help implement these strategies with their partners!

The results from the transcripts suggest that imitating the strategies of others (strategy 1) and discovering the optimal solution by within-group conversation (strategies 2–6) were the main drivers of learning for the teams. In the next section we build upon this observation when we compare team learning with individual learning.

7.4. The Relative Impact of Past Own vs. Other Behavior in the Auctions

For Studies 2a and 2b, we calculated the fraction of bids that were placed on the correct solutions (SOL) for each individual/team in each period t. We regressed SOL in period t on (a) SOL of the same person/team in period $t-1$ and (b) the average SOL of the other individuals/teams on the same market in period $t-1$.[11]

The results show that past performance of the *other players* is always a better predictor of both individual and team performance than past own behavior, which demonstrates that there is learning from the behavior of others in the market. More relevant for our purposes, the effect of past own behavior is more pronounced for teams than for individuals. The OLS regression ($R^2 = 0.47$) for individuals is $\text{SOL}(t) = 0.04 - 0.02\ \text{SOL}(\text{own } t-1) + 0.92\ \text{SOL}(\text{others } t-1)$. The OLS regression for teams ($R^2 = 0.33$) is $\text{SOL}(t) = 0.09 - 0.07\ \text{SOL}(\text{own } t-1) + 0.78$

[9] We do not have video transcripts of Studies 2b and 3. This fact precludes the possibility that the better performance of teams and better learning transfer in teams might have been driven by a potential effect of being videotaped (being videotaped might have induced more engagement in the task to "show off" the team's smartness). Given that the basic insights from Studies 2a, 2b, and 3 are the same, we can rule out that videotaping in Study 2a had any noticeable effect on performance.

[10] We performed a reliability check of the classifications by double rating 10% of the videotapes. The interrater agreement between two independent raters (who were unaware of the study goals) was 94%, corresponding to $\kappa = 0.88$ with a 95% confidence interval from 0.71 to 1.00.

[11] This analysis is based only on Studies 2a and 2b involving the combinatorial auctions, because inferring trading strategies from the double auctions (of Study 3) would be more ambiguous.

Table 2 Frequency of Topics Discussed by the Teams in Study 2a (Content Analysis)

Classification of discussion topics	Before period 1	Periods 1–10	Periods 11–20	Periods 21–30	Sum (%)
1 Submit the same bid as others	0	58	17	20	95 (29.3)
2 Putting oneself in the position of others	4	29	10	10	53 (16.4)
3 Inferring solution from auction	4	41	7	1	53 (16.4)
4 Strategic elimination of incorrect answers	9	20	7	0	36 (11.1)
5 Demonstrability of correct solution	19	10	2	1	32 (9.9)
6 Seeking confirmatory evidence	25	3	0	0	28 (8.6)
7 Seeking nonconfirmatory evidence	14	3	0	0	17 (5.2)
8 Compromise by alternating strategies	5	5	0	0	10 (3.1)
Sum	80	169	43	32	324 (100)

SOL(others $t-1$). The performance of the other players is a significant predictor in both regressions, whereas one's own performance is only significant for the teams, which suggests that teams depend relatively less on learning from others or, put differently, rely more on their own past performance through the processes listed in Table 2.[12]

8. General Discussion and Conclusion

We have studied the impact of team decision making on market behavior and on subsequent individual performance for two seminal intellective tasks, the Monty Hall problem and the Wason selection task. Whereas there has been considerable research comparing the nature and quality of the decisions made by individuals and teams (see, e.g., Bornstein et al. 2004, 2008; Bornstein and Yaniv 1998; Cooper and Kagel 2005; Feri et al. 2010; Kocher and Sutter 2005), there has been no work on the effects of being on a team in competitive environments on subsequent individual decisions.

Ours is the first paper to study systematically the net advantage of minimal ($n = 2$) teams over individuals during and after participation in competitive markets. Remarkably, our results show that under identical competitive incentives, teams lead to considerably superior learning compared to individual traders, and we infer that the learning from teams involved in competitive markets is superior to learning from cooperative teams in noncompetitive settings (Maciejovsky and Budescu 2007). Moreover, we find that teams of traders price the assets closer to the rational level, and they learn the correct solution faster than individuals, and achieve this with less specific performance feedback. Teams can even beat a very high threshold—the truth wins norm—possibly because they analyze more carefully the more complex problems.

The main contribution of our paper is in documenting the knowledge transfer from team decision making to subsequent individual tasks, something that is of general relevance for all organizations that need to decide whether the workplace organization is more team oriented or more individualistic. We found a tremendous difference in the individual postmarket behavior between people who traded individually and those who traded as part of a team: People who traded as members of a team outperformed those who traded individually. This effect was even observed five weeks after the original interaction took place (Study 1). The net "team effect" (i.e., the advantage of a team member over an individual trader) was significant in Studies 2b and 3, where the opportunities for learning were shorter and feedback was less precise. In these two studies combined, the transfer rate was 27% for participants who traded individually, and approximately 48% for those who traded in dyads.

Table 3 summarizes the rate of transfer for individuals and teams across all three studies (Stage III). We classify the transfer scores into three categories: Scores of 0–1 suggest no (or almost no) transfer, whereas scores of 6–7 in the Monty Hall study and 7–8 in the Wason studies indicate perfect (or almost perfect) transfer. The intermediate level suggests mixed results, but only a minority (24%) of the subjects falls in this group. The overall distribution is almost symmetric, with essentially equal numbers of people in the no transfer and perfect transfer categories, but the pattern is different in the two groups: The modal classification for INDIVIDUAL is no transfer (46%),

Table 3 Distribution (in %) of Number of Correct Solutions in the General Transfer Task (Stage III) Across Studies and Experimental Conditions

Correct solutions	Individuals	Teams	Total
No transfer: 0–1 (Monty Hall and Wason selection)	**46.00**	32.75	31.17
Partial transfer: 2–5 (Monty Hall)/ 2–6 (Wason selection)	25.50	23.50	24.17
Perfect transfer: 6–7 (Monty Hall)/ 7–8 (Wason selection)	28.50	**43.75**	38.67
Sample size	200	400	600

Note. The modal category is in bold.

[12] Hierarchical linear model regressions with random intercepts confirm this pattern.

whereas for TEAMS it is perfect transfer (44%), and the two distributions are significantly different ($\chi^2(2) = 14.54$, $p < 0.05$). Thus, we can safely conclude that the experience of team decision making increases individual problem solving skills.

The identification of knowledge spillovers from team decision making to subsequent individual behavior (and the associated enhanced problem-solving skills) has important managerial implications. It supports the use of teams in organizational tasks not only as a means to achieve better decisions, but also as an important and relatively cheap training tool to improve the skills of employees in individual tasks. Moreover, our specific focus on the analysis of trading behavior in competitive auctions and markets suggests that even for financial and investment decisions, which have traditionally been motivated by individual incentives, team decisions might improve performance.

Acknowledgments
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