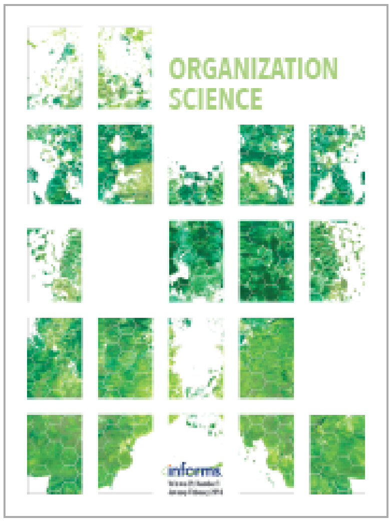

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Too Much Trust in Group Decisions: Uncovering Hidden Profiles by Groups and Markets

Boris Maciejovsky,[a] **David V. Budescu**[b]

[a] School of Business, University of California, Riverside, Riverside, California 92521; [b] Department of Psychology, Fordham University, Bronx, New York 10458

Contact: borism@ucr.edu (BM); budescu@fordham.edu, https://orcid.org/0000-0001-9613-0317 (DVB)

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Abstract. A crucial challenge for organizations is to pool and aggregate information effectively. Traditionally, organizations have relied on committees and teams, but recently many organizations have explored the use of information markets. In this paper, the authors compared groups and markets in their ability to pool and aggregate information in a hidden-profiles task. In Study 1, groups outperformed markets when there were no conflicts of interest among participants, whereas markets outperformed groups when conflicts of interest were present. Also, participants had more trust in groups to uncover hidden profiles than in markets. Study 2 generalized these findings to a simple prediction task, confirming that people had more trust in groups than in markets. These results were not qualified by conflicts of interest. Drawing on experienced forecasters from Good Judgment Open, Study 3 found that familiarity and experience with markets increased the endorsement and use of markets relative to traditional committees.

Supplemental Material: Data and the online appendix are available at https://doi.org/10.1287/orsc.2020.1363.

Keywords: trust • markets • groups • decision making • prediction markets

A key role of organizations is to process information generated by individuals and groups to undertake interdependent activities (Puranam et al. 2012). As such, organizations are systems that solve coordination problems (Garicano 2000) through gathering, interpretation, and synthesis of information (Tushman and Nadler 1978), as well as through communication (Thompson 1967) and the sharing of knowledge (Kogut and Zander 1992). Often this process of pooling and aggregating information and knowledge involves the use of teams and committees, particularly for complex and difficult tasks (Salas et al. 2008).

Given the increasing prevalence of using teams, committees, and ad hoc groups for decision making in modern organizations, questions of how to achieve effective information sharing and collective learning to boost organizational performance have captured the interests of academics and practitioners (Morgeson et al. 2010). Recently, this drive to improve information flow and learning has led to the use of internal information markets in a variety of organizations, such as Ford, Google (Cowgill and Zitzewitz 2015), Hewlett-Packard (Gillen et al. 2013), and Nokia (Hankins and Lee 2011).

The two institutions—groups and markets—differ in many important ways. First, the setting is markedly different. Ad hoc groups (but also teams and committees) typically operate in face-to-face settings with unregulated communication patterns, whereas markets are highly structured and are usually implemented electronically on networked computers. Equally important, participants' motivations can vary; the implicit assumption in group decision making is that the group members have aligned incentives, with shared goals and cooperation. In contrast, markets are competitive and allow for conflicting goals. Thus, traders may wish to withhold private information that they believe would benefit them during trading. Despite the surging interest in groups and markets, surprisingly little is known about the conditions under which they perform well and the circumstances under which one outperforms the other. The purpose of this study is to fill this gap in the organizational research literature.

One recent exception is the work by Atanasov et al. (2017), who conducted a large-scale long-term experimental test of prediction markets and prediction polls. They found that market prices were more accurate than simple mean forecasts based on estimates from polls (Atanasov et al. 2017). However, polls outperformed markets when statistical aggregation techniques that included temporal decay, differential weighting based on past performance, and recalibration were used. There is also a sparse, but growing, literature that seeks to extend understanding of group decision making by introducing more realistic assumptions about group members. Specifically, group members are assumed to have less than perfectly aligned incentives (Wittenbaum et al. 2004, Toma and Butera 2009).

In this paper, we build on this foundation and compare the performance of groups and markets to better understand their respective advantages and shortfalls (Maciejovsky and Budescu 2007, 2013; Atanasov et al. 2017). To achieve this goal, we seek to understand conditions that attenuate differences between performance levels of groups and markets. Consequently, we introduce and manipulate conflict of interest between group members and traders. A novel aspect of our work is the investigation of participants' perceptions, by measuring their level of trust in the ability of groups and markets to pool and aggregate information effectively, and the accuracy and validity of these subjective assessments, that is, how they relate to the institutions' actual performance.

Group Decision Making

Group decision making has increased in popularity in organizations and is well received by management and employees (Salas et al. 2008). For example, teams lead to more employee involvement and satisfaction (Wellins et al. 1994), as well as better performance (Salas et al. 2007). However, they also pose a challenge. Superior individual performance increases the probability of promotion (Medoff and Abraham 1980, 1981) and receiving higher compensation (McCue 1996). This suggests that individuals have incentives to strategically withhold information from the team to gain, or maintain, their informational advantage (Mitusch 2006).

Despite this inherent mismatch between employee goals and organizational goals, the majority of research on group decision making has assumed that group members cooperate and share information voluntarily (Kerr and Tindale 2004, Adamowicz et al. 2005, Tindale and Kluwe 2015). This literature has generated many important insights, showing that groups outperform individuals in intellective tasks, allowing for knowledge transfer from group to individual settings (Maciejovsky and Budescu 2007, Laughlin 2011). Compared with individuals, groups make more accurate hiring decisions (Tindale 1989), recall information more accurately (Hinsz 1990), obtain better negotiation outcomes (Morgan and Tindale 2002), generate more creative ideas (Nijstad and Paulus 2003), and provide more accurate forecasts (Kerr and Tindale 2011, Mellers et al. 2014). In some intellective tasks, groups even outperform the best individual member (Laughlin et al. 2003, Cooper and Kagel 2005, Laughlin et al. 2006, Maciejovsky et al. 2013).

The effect of group decisions on information processing and learning can also be analyzed in the context of organizational structure. Puranam and Maciejovsky (2017) provide a framework for analyzing how organizational design, specifically interaction patterns and influence structures, impacts information processing. The most basic setting is one where decision makers are highly interconnected and share decision-making power. This setting characterizes many decentralized organizational decisions seen in task forces, hiring committees, and work groups. Examples include banks choosing which loans to fund, venture capital firms and mutual funds selecting investments, movie studios evaluating scripts, and top management teams deciding which strategic projects to pursue (Csaszar 2012). The dominant experimental paradigm that captures the structural underpinnings of these settings is the hidden-profiles paradigm (Stasser and Titus 1985).

The Hidden-Profiles Paradigm

In the hidden-profiles paradigm, the relevant information for the solution to a problem is distributed unevenly across group members (Stasser and Titus 1985). Some information is shared by multiple (possibly all) group members, whereas other information is available only to some group members. After being endowed with informational profiles—consisting of some common and some unique pieces—all group members are allowed to discuss the decision problem. The information is distributed such that the correct solution (i.e., the hidden profile) surfaces if, and only if, all group members share all the information—common and private. Reliance on privately held information as well as pooling only the shared information leads to suboptimal solutions. The seminal finding in the literature is that groups typically fail to pool all the information, and instead focus too much on shared information at the expense of private information (e.g., Lu et al. 2012).

This preference for shared information is called the common-knowledge effect (Gigone and Hastie 1997). Research on hidden profiles suggests five basic principles and empirical regularities. First, a simple information-sampling model correctly predicts that common information is more likely to be shared than private information (e.g., Stasser and Titus 1987, Hinsz 1990). Second, premature closure and the desire to reach consensus plays a role in this effect (e.g., Karau and Kelly 1992, Kruglanski and Webster 1996). Third, people prefer to both receive and present commonly shared information (e.g., Wittenbaum et al. 1999). Moreover, people are perceived as more knowledgeable, competent, and credible when the shared information is already known by others (Kerr and Tindale 2004). Fourth, people are reluctant to change their initial position, derived from the privately held information (e.g., Brodbeck et al. 2002, Greitemeyer and Schulz-Hardt 2003). Finally, shared information is more likely to be recalled, so the failure to pool privately held unique information may simply be the result of forgetting the unique information (Lightle et al. 2009).

Most of the work on hidden profiles is based on decentralized groups, in which the members are symmetric in terms of power and status (Puranam and Maciejovsky 2017). A crucial implicit assumption is that group members share a common goal and have aligned incentives. However, in the context of organizational decision making, this implicit assumption seems questionable (Toma and Butera 2009, Pearsall and Venkataramani 2015). Well-functioning organizations require and expect employees to contribute to the overall organizational goals (Puranam et al. 2014), but this does not prevent opportunistic behavior such as strategic information sharing or distortion of information to gain an advantageous position (Wittenbaum et al. 2004).

Hollingshead et al. (2005) demonstrated that individuals with competitive incentives often strategically distort information to promote their preferred solution, and Toma and Butera (2009) showed that competition among group members resulted in the withholding of unshared information, which was crucial for the optimal solution. Maciejovsky and Budescu (2013) introduced side payments that created conflicts of interest between group members and demonstrated that information sharing, which is necessary for learning and knowledge transfers, largely breaks down. In fact, the presence of relationship conflicts during a task conflict increased group members' rigidity to hold onto suboptimal initial preferences (De Wit et al. 2013).

The hidden profile paradigm is highly relevant for organizational decision making in a variety of domains, ranging from collaboration and conflict to learning and the formation of network structures. Cramton (2001) suggested that differences in the situations, contexts, and constraints of dispersed collaborators constitute hidden profiles that might undermine team cohesion and limit collaboration. Task conflicts that are expressed as debates rather than disagreements lead to more information sharing, because receivers perceive senders to be more receptive to dissenting opinions (Tsai and Bendersky 2016). How prior knowledge is organized affects the interpretation of information and might lead to adverse effects on learning transfer (Lewis et al. 2005). Shore et al. (2015) allowed for clustering of members in a hidden-profiles task to identify the conditions under which network structures form and the type of explorations they yield.

Typically, groups outperform individuals (e.g., Koriat 2012), yet groups can make ineffective decisions in hidden-profiles tasks (Wittenbaum and Stasser 1996) and in shared task representations (Tindale et al. 1996) unless they are highly cohesive, or have strong and directive leaders. Group members may also face coordination difficulties, suffer from motivational losses (Steiner 1972) or negative moods (van Knippenberg et al. 2010), and be silent, thereby withholding important information from others (Gavetti et al. 2012, Schilling and Fang 2014).

To summarize, the hidden-profiles paradigm captures the fact that knowledge in organizations is dispersed asymmetrically, and empirical studies show that dissemination and aggregation of information is often limited and compromised due to conflicts of interest among group members.

Recently, information (or prediction) markets[1] have been used by various organizations as an alternative mechanism. Next, we discuss how these markets work, and review some of their properties.

Information Markets

Information markets allow participants to trade contracts that offer payments contingent on the outcome of specific events. For instance, these markets allow participants to acquire and trade contracts (or assets) that pay \$1 if an event occurs by a prespecified date, and \$0 otherwise. A market price of \$0.64 is interpreted as representing a 64% chance that the target event will occur. These events can be uncertain, allowing the market essentially to forecast future events (e.g., the winners of elections or sport events), or they can be solutions to certain intellective problems. In the latter case, the market provides a mechanism for traders to discover the solution by pooling and aggregating the beliefs of all market participants. Markets provide incentives for truthful revelation and information discovery by having participants "put their money where their mouth is" (Hankins and Lee 2011, p. 1). As such, they do not require organizational and employee goals to be aligned. Thus, both correct and incorrect decisions have direct financial consequences.

A vast literature shows that such markets can be effective in pooling and aggregating information. In a seminal study, Plott and Sunder (1982) allowed traders on an experimental asset market to obtain one of two possible dividends, contingent on the state of nature, which was randomly determined. Although only half of the traders were informed about the actual state of nature, market prices revealed the true state, demonstrating that markets can disseminate private information effectively. Plott and Sunder (1988) also showed how markets successfully aggregate information. Traders were informed that one of three possible states of nature (X, Y, and Z) would determine dividend payments, and they received incomplete private information. For instance, when the true state of nature was X, half of the traders were informed that the state was not Y, whereas the other half were told that it was not Z. Market prices were able to properly combine these incomplete cues and revealed that the true state of nature was X (Plott and Sunder 1988).

The ability of markets to pool and aggregate information effectively relies on a diverse pool of traders with heterogeneous beliefs (Sethi and Vaughan 2016), a sufficient number of traders (Othman and Sandholm 2010), and incentives to trade (Polgreen et al. 2007). Features that might render markets vulnerable to failure include large numbers of unrepresentative traders (e.g., noneligible voters in political prediction markets), overly homogenous markets (Levine et al. 2014), budget limitations by individual traders, social influence (Lorenz et al. 2011), and strongly invested traders with a desire for a particular outcome (Rothschild 2009, Rothschild and Sethi 2016).

The promise of markets to pool and aggregate information effectively has increased interest (Wolfers and Zitzewitz 2004) and prompted their implementation in a variety of high-profile organizations, including the U.S. Department of Defense and multibillion dollar corporations (Arrow et al. 2008), as well as in professional communities such as the Social Science Replication Project (Camerer et al. 2018). The performance of these markets is generally encouraging. An internal prediction market at Ford outperformed expert forecasts of weekly vehicle sales, achieving a 25% lower mean squared error (Cowgill and Zitzewitz 2015). An internal prediction market at Intel outperformed Intel's official forecast, and the performance of the market was particularly impressive over short forecast horizons (Gillen et al. 2013). Dahan et al. (2011) showed that respondents not only preferred taking part in a market game (securities trading of concepts [STOC]) compared with filling out surveys, but that the market was also more cost-efficient and easier to scale to multiple concept tests in a series of market research applications. Chen and Plott (2002) showed in the case of Hewlett-Packard that markets aggregate information with respect to sales forecasts more effectively than traditional business methods, such as meetings. Although prediction markets work well, they do not always outperform alternative methods, such as the statistical aggregation of individual forecasts (see Goel et al. 2010, Atanasov et al. 2017 for examples).

Interestingly, despite these success stories, many corporations appear to be reluctant to implement and roll out market mechanisms widely (Croxson 2011). Only a small minority (9%) of 1,695 executives from many industries and regions, who reported using prediction markets in their organizations, had measurable benefits (McKinsey 2011). One barrier to adoption might be that the legal requirements are opaque and restrictive. Intrade, for instance, shut its operations after it was sued by America's Commodity Futures Trading Commission (CFTC), because it allowed traders to place bets on products, such as gold and oil, which are regulated by the CFTC (*The Economist* 2012). Another challenge arises in the recruitment and maintenance of market participants. Evidence from the Good Judgment Project indicates that whereas it was easy to recruit and maintain a large pool of participants for the forecasting teams using a traditional survey platform, interest in participating in a parallel prediction market treatment was lower; more than half of the participants expressing an interest to switch from the market to the team (Good Judgment Project 2015). Markets are also perceived to be harder to understand and appear less transparent (Broughton 2013), which might contribute to a reluctance to implement them.

Contrasting Groups and Markets

Laughlin (1999) formulated 12 postulates that characterize the process of collective induction for cooperative groups, including the search for descriptive, predictive, and explanatory generalizations, rules, and principles. Postulates 1–6 describe the general social combination processes of group decision making. Postulates 7 and 8 deal with group hypothesis formation, and postulates 9–12 summarize research on collective versus individual induction, influence patterns, the importance of multiple hypotheses and multiple evidence, and the effectiveness of positive and negative hypothesis tests.

Maciejovsky and Budescu (2007) used Laughlin's framework to compare groups and markets and argued that many of the central postulates that describe collective induction in cooperative groups (Laughlin 1999) also apply to markets. For instance, postulates 3 and 5, taken together, suggest that groups can identify the correct solution, even when only a small minority of participants knows the correct response. Postulate 9 states that the solution, identified by groups, is as good as the best solution proposed by one of its members. Postulate 4 lists the conditions required for the demonstrability of the solution: (a) the group shares a conceptual system (rules, terminology, etc.), (b) the group has sufficient information to identify the solution, and (c) members who endorse incorrect solutions are able to rectify their mistakes when shown the correct solution. All these postulates apply equally to most information markets and suggest that both institutions support the emergence of a shared mental model (Mantzavinos et al. 2004). In groups, this shared model is the result of free communication, whereas in markets it is based on the information revelation that is generated by traders who compete for shares and dividends.

The most salient difference between groups and markets pertains to postulate 4(d), which states that group members who know the correct solution have the ability, time, and motivation to demonstrate it to their fellow group members. This is a necessary condition for groups, but not for markets. In markets, conflicting incentives reinforce the desire to withhold information from fellow traders (e.g., the correct solution to a problem) in order to benefit from future dividend payments.

Maciejovsky and Budescu (2007) compared the ability of interactive groups and markets to solve the Wason's selection task (Wason 1966). This task involves four cards, designed to test a logical statement of the form "if p, then q." The four cards show "p," "q," "not p," and "not q." The correct solution involves turning over the "p" card to check whether it shows "q" on the other side and the "not q" card to check whether it does not show "p" on the other side. The authors showed that markets could pool information effectively, allowing people who initially failed to solve the task to infer its correct solution during, and after, trading. In the markets, the participants were provided with equal numbers of the four cards, and traded them with the understanding that those who held cards that constituted the correct solution would receive financial dividends. Under certain conditions, markets performed as well as groups in identifying the solution. Their success can be attributed to the effect of payoff feedback (the dividends), and information spillovers from those traders, who knew the solution, to those who did not know it (Budescu and Maciejovsky 2005).

The distinctive property of markets is that one can benefit from information only by acting on it (e.g., by buying assets that one expects will appreciate in value and/or selling assets that will depreciate); however, by acting on such information, one sends a signal to other traders, allowing them to infer one's knowledge. These traders can then imitate the behavior, and the value of the information diminishes as it gets shared, ultimately making information public knowledge, which is fully reflected in market prices.

Another important difference between groups and markets relates to the nature of communication. In group interactions, the flow of communication is typically free and unrestricted, whereas markets utilize rules that standardize social interaction and communication among participants. These rules determine how information is submitted to the market (e.g., by submitting and/or accepting bids and/or asks) and how inferences about underlying beliefs of traders are made (e.g., by tracking market prices or market volume).

Groups and markets also differ in the interaction setting. Groups typically interact face to face, using verbal and nonverbal communication, which is important in negotiation and bargaining encounters that reflect information asymmetries and conflicts of interest (for a review, see Thompson et al. 2010). Modern markets, in contrast, are typically anonymous and are frequently conducted in computer-mediated settings. These settings, like group decision support systems, can reduce barriers to participation in group discussions (DeSanctis and Gallupe 1987, Dennis et al. 1988, McLeod 1992) and promote minority opinions (McLeod et al. 1997). A similar effect was shown for anonymity, which also reduced social barriers to communication by reducing the effects of evaluation apprehension and social status differences (Valacich et al. 1992). There is a downside to computer-mediated interactions that might explain the limited implementation of information markets in organizations; the interactions are structured, governed by strict rules, anonymous, less natural, more intimidating, and less trustworthy (Ba and Pavlou 2002). Similarly, lack of experience and familiarity with information markets might also undermine people's trust in this institution (Gefen and Straub 2004).

Despite the surge of interest in markets and groups, there has been no prior research investigating how much trust people have in the ability of these institutions to pool and aggregate information effectively and, more importantly, the accuracy and validity of these subjective assessments, that is, how they relate to the institutions' actual performance. This paper provides a first step in filling this gap in the literature.

The Present Studies

Following a systematic replicate-and-extend strategy, we present the results of three experimental studies that demonstrate that people trust groups more than markets to pool and aggregate information effectively. We show that groups outperform markets when the members' incentives are aligned and they share common interests; however, markets outperform groups in the presence of conflicts of interest between their members. Most interestingly, we find a clear disconnect between the institutions' performance and the participants' perceptions. People appear to be relatively insensitive to the detrimental effect of intragroup conflict on group performance and, generally, trust groups more than markets.

The current work is based on a specific type of market setting (double auction), a specific group setting (face-to-face communication), and a specific task type (hidden profiles). Future research is needed to investigate the generality of these findings for different settings and tasks. Nevertheless, our findings provide an important contribution to the literature, as they help explain why markets have been relatively underutilized by organizations. Although our markets outperformed groups in the presence of conflicts of interests, the very features that made them successful also made them less appealing and trustworthy to our participants. In general, groups were perceived to be more natural, benevolent, better, and more familiar than markets; however, personal experience with markets increased people's endorsement and use of markets relative to group settings.[2]

Method

Study 1

Participants. Four hundred and fifty students (240 females, $M_{\text{age}} = 22.30$, $SD_{\text{age}} = 2.04$) from Imperial College London participated in a laboratory study, lasting between 60 and 90 minutes.

Experimental Design and Procedure. Participants were randomly assigned to groups of three, which, in turn, were assigned to one of 10 between-subjects conditions (see Table 1 for a list of experimental conditions). They were defined by crossing the two types of institutions (groups or markets) and the presence and strength of explicit manipulation inducing conflicts of interest (no manipulation, weak, or strong). We built on the experimental paradigm by Maciejovsky and Budescu (2013) with two important differences. First, we systematically varied the degree of explicit manipulation. Second, we tested the effects of pro and con arguments when introducing the manipulations. We will describe the design in detail after describing the experimental task.

The Task. Participants were told that their task would be to choose the best of three applicants (labeled A, B, C) for a managerial position. They were given information about five characteristics of the three applicants: interpersonal skills, personal skills, experience, intelligence, and motivation. Participants were informed that there was no uncertainty or ambiguity regarding the profiles and evaluations, and that all characteristics should carry equal weight in the evaluation of the candidates. We used a compensatory incentive scheme (adapted from Lightle et al. 2009):

$$\begin{aligned} \textit{Strength of an applicant} &:= 2^*(\#\,\textit{of positive characteristics}) \\ &\quad - 1^*(\#\,\textit{of negative characteristics}). \end{aligned}$$

This incentive scheme allowed participants to unambiguously determine the strength of each applicant. Candidate B was objectively the best, with three positive evaluations and two negative ones; Candidate A was the second best applicant and C was the weakest applicant. However, each participant only received three of the five values of each applicant (see Table 2 for the distribution of cues across participants and applicants).

The experimental conditions consisted of five interactive groups and five markets. First, we describe the procedure for the group conditions.

The Groups. After reading the instructions and completing a short quiz that tested the understanding of the instructions, participants were randomly assigned to one of three roles (labeled 1, 2, or 3) in the group. They were given the respective information, consisting of three of the five pieces of information for each of the three applicants (see Table 2), and were asked to rank the applicants from best to worst, individually.

Then, participants turned to their groups, and were allowed to discuss the applicants for five minutes. Groups were not asked to provide an overall ranking of the applicants, but after the group interaction, participants reranked the applicants individually and privately, and rated their trust in the group's ability to pool all the relevant information ("How much trust do you have that the group identified the best applicant?"), using a five-point Likert scale, ranging from 1 = no trust at all to 5 = a lot of trust.

Table 1. Experimental Conditions (Study 1)

Manipulation implemented	Institution: Groups	Institution: Markets
None (control)		
Weak Buy		
Weak Sell		
Strong Buy		
Strong Sell		

Table 2. Applicant Characteristics and Information Distribution (Study 1)

	Info for participant 1			Info for participant 2			Info for participant 3		
Attributes	A	B	C	A	B	C	A	B	C
Interpersonal	+	+		+		+		+	+
Intelligence		+	+		+		—		+
Motivation	—	—				—	—		—
Personal			—	—	—	—		—	
Experience	+		—	+	+		+	+	

All participants received a show-up fee of £10 and were told that additional performance payments would be offered. Specifically, participants received £4 if a majority (two or more) of the group members ranked the best applicant highest. Their additional payments varied across experimental conditions, as we explain in the next paragraphs.

Control Group (Without Manipulation). Participants received their show-up fee and the £4 if a majority of members ranked the best applicant (B) highest.

Weak Manipulation. In half of the groups of this condition, we provided incentives to one member, the one assigned to role 1, to convince the others to rank A the highest and, in the other half of the groups, not to rank A the highest. We did this to test whether participants would be more successful in convincing others with respect to pro arguments than with con arguments.

In both sets, participant 1 was promised a private side payment of £5 if the participant's manipulation attempt was successful. Specifically, in the pro case, if two or more participants ranked A highest, participant 1 received £5 and the others received nothing. In the con setting, if two or more of the participants did not rank A highest, participant 1 received £5 and the others received nothing. As always, if B received a majority of votes, all participants received a payment of £4. This setting captured the idea of a knowledge-sharing dilemma that characterizes many organizations. Individual incentives (£5) are in conflict with group-level incentives (£4 for everyone) and undermine the social optimum (£12 for the group).

Strong Manipulation. In half of the groups of this condition, we provided incentives to all three members. Participants assigned to roles 1 and 2 were incentivized to convince the others to rank A the highest and participant 3 to convince the others to rank C the highest. In the other half of the groups, we provided incentives to participants 1 and 2 for convincing the others not to rank A the highest and to participant 3 for convincing the others not to rank C the highest. If successful, participants received private side payments of £5. Specifically, in half of the groups, if all three participants ranked A the highest, participants 1 and 2 received £5 and participant 3 received nothing. If two or more voted for C, participant 3 received £5 and the others nothing. In the other groups, if all three participants voted for a candidate other than A, participants 1 and 2 received £5 and participant 3 received nothing. If two or more did not vote for C, participant 3 received £5 and the others nothing. As always, if candidate B received a majority of votes, all participants received a payment of £4. This setting also captured the idea of a knowledge-sharing dilemma, as individual incentives are in conflict with group-level incentives.

The Markets. Participants traded shares of the three applicants in a computerized double auction, implemented with the software z-Tree (Fischbacher 2007). Figure 1 shows a schematic screenshot of the market. Prior to market opening, participants traded shares on a trial market. The experiment started after all participants solved correctly all the items of a short quiz designed to test their understanding of the instructions.

Markets consisted of 10 trading periods, during which participants could buy and sell shares of the three applicants simultaneously in a continuous double auction. At the beginning of each trading period, every participant received an endowment of 200 experimental currency units (ECUs), with an exchange rate of 100 ECUs = £2. They were also endowed with six shares: two shares of each of the three applicants A, B, and C.

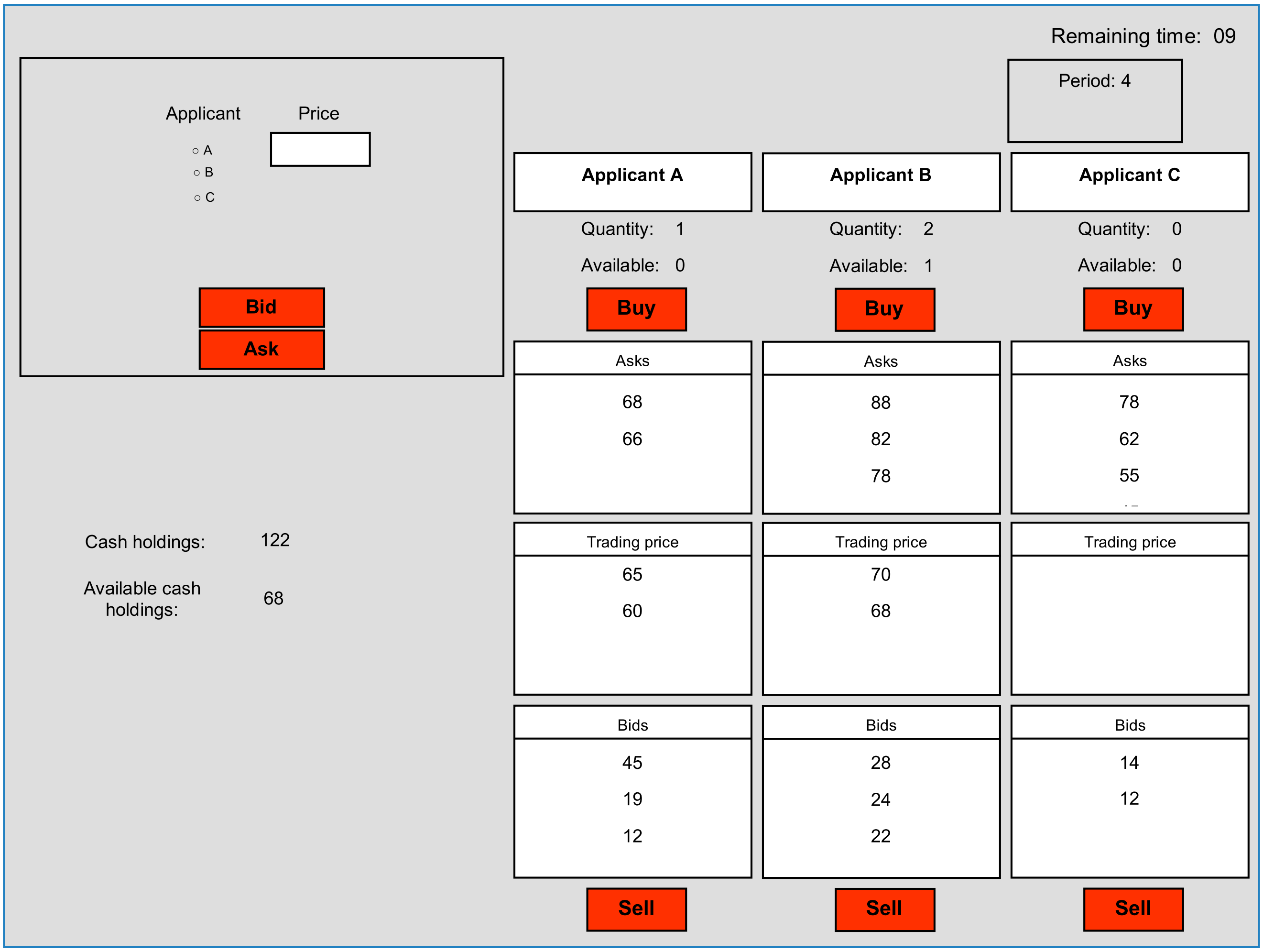
Each trading period lasted for 180 seconds. During that time, participants could submit buying offers (bids) or selling offers (asks) or accept offers submitted by other participants. A chronological list of concluded trades for each applicant was shown to all the participants during trading, along with a list of all current bids and asks. Participants were also informed about their cash holdings, their shareholdings, the remaining trading time, and the current period number. Participants were not granted credit, so could not make offers that exceeded their current cash endowments, and were not allowed to sell shares that they did not possess (no short-selling).

All participants received a show-up fee of £10. If participants held shares of the best applicant (B) at the conclusion of a trading period, they received dividend payments of £2 for each share held (since each participant held two shares of B at the outset of trading, dividends would be £4 in that case and would be equivalent to the incentives offered in the control group). Dividends were paid out at the end of the experiment, based on the results of one, randomly determined, period. To induce active trading, participants were informed that only dividends earned would be converted to cash, so they could not simply cash in their endowments from the markets. Side payments to participants varied across experimental conditions, as explained in the next section.

Control Market. In the control market (no manipulation), participants only received the show-up fee and their dividends (if any), based on the one period, which was randomly selected at the conclusion of the market.

Weak Manipulation. In addition to the participation fee and the dividend payments (£2 per share of the

Figure 1. (Color online) Schematic Screenshot of the Market (Study 1)



best candidate on the period selected), participants could earn additional side payments, similar to the group conditions. To contrast incentives for pro and con arguments in the markets, we provided incentives for buying shares in half of the markets and for selling shares in the other half of the markets. In half of the markets, participant 1 received a private side payment of £2.50 per share if the participant bought a share of applicant A. If the participant bought two shares, the amount received would be £5 (which was equivalent to the financial incentives offered in the group conditions). In the other markets, participant 1 received a private side payment of £2.50 per share sold of applicant A, and if the participant sold two shares, the amount received would be £5.

Strong Manipulation. Participants received the flat show-up fee and dividend payments (£2 per share of the best candidate for the randomly selected period). In half of the markets, we provided incentives for buying shares of candidates and, in the other half of the markets, for selling shares of candidates. In half of the markets, participants 1 and 2 received a private side payment of £2.50 per share if they bought a share of applicant A, and participant 3 received a private side payment of £2.50 per share for buying a share of applicant C. In the other markets, participants 1 and 2 received a private side payment of £2.50 per share if they sold a share of applicant A, and participant 3 received a private side payment of £2.50 per share for selling a share of applicant C.

After the last period of the market, and before receiving the final payoffs, participants were asked to rank, again, the three applicants privately and to rate their trust in the market's ability to pool all relevant information ("How much trust do you have that the market identified the best applicant?"), on a five-point Likert scale, ranging from 1 = no trust at all to 5 = a lot of trust.

Results. ***Learning on the Markets.*** We computed the bid-ask spread, defined as the total amount of money submitted as selling offer minus the total amount of money submitted as buying offer on a candidate per participant per period. The lower the bid-ask spread, the more liquidity the market displays for an asset and it is also more competitive. For our purpose, it is an indication of competitive pressure for the shares of a candidate. The results of a repeated measures analysis of variance (ANOVA) with the repeated factors *candidate* (correct vs. incorrect candidates) and *periods* (1–5 vs. 6–10), as well as the between-subjects factors *manipulation* (weak vs. strong) and *incentive format* (sell vs. buy), showed significant main effects for candidate ($F(1,55) = 79.91$, $p < 0.001$, $\eta^2 = 0.0.60$) and period ($F(1,55) = 7.91$, $p = 0.007$, $\eta^2 = 0.0.13$), as well as for the interaction of *candidate* × *incentive format* ($F(1,55) = 722.66$, $p < 0.001$, $\eta^2 = 0.0.29$) and *candidate* x *periods* ($F(1,55) = 6.25$, $p = 0.015$, $\eta^2 = 0.0.10$). The interaction between candidate and incentive format indicated that the bid-ask spreads for the correct candidate relative to incorrect candidates was smaller under selling than buying incentives. The interaction between candidate and periods indicates that the bid-ask spreads for the correct candidate relative to incorrect candidates was smaller in the second half of trading thank in the first half.

Choice of the Best Candidate. For each group/market, we calculated the proportion of (post group or market interaction) votes for the best applicant, B. This measure ranged from 0 to 3 (as each group/market consisted of three participants). The results of an ANOVA on this measure of *votes for applicant B* as the dependent variable and *institution* (groups, markets) and *manipulation* (control, weak buy, weak sell, and strong buy, or strong sell) as between-subjects factors showed a significant main effect for *manipulation* ($F(4, 140) = 11.25$, $p < 0.001$, partial $\omega^2 = 0.24$). There was no significant difference between the institutions, but there was a significant interaction between *institution* and *manipulation* ($F(4, 140) = 3.56$, $p = 0.005$, partial $\omega^2 = 0.06$). See Figure 2 for a graphical depiction of the interaction.

To unpack the interactions, we analyzed a set of preplanned contrasts. We found that (1) the strong manipulation was more effective than the weak one ($F(1,140) = 8.33$, $p = 0.005$, partial $\omega^2 = 0.05$); (2) instructions to sell were more effective than instructions to buy ($F(1,140) = 17.33$, $p < 0.001$, partial $\omega^2 = 0.10$), presumably because buying is encoded as a loss; and (3) the impact of the stronger manipulation was more pronounced in the sell condition ($F(1,140) = 5.04$, $p < 0.05$, partial $\omega^2 = 0.03$). Finally, and most importantly for our purpose, (4) there was a significant interaction between the institution and the presence of manipulation ($F(1,140) = 11.52$, $p < 0.001$, partial $\omega^2 = 0.07$). Groups outperformed markets in the control condition but markets outperformed groups in the presence of manipulations. A good illustration of this interaction is displayed in Table 3, which shows the number of teams with perfect solutions (i.e., all three participants selected the best candidate, B).

Trust. The results of an ANOVA with individual *trust* as the dependent variable and *institution* (groups, markets) and *manipulation* (control, weak buy and sell, and strong buy and sell manipulations) as between-subject factors showed a significant main effect for *institution* ($F(1, 440) = 27.33$, $p < 0.001$, partial $\omega^2 = 0.06$; $M_{\text{group}} = 3.52$ vs. $M_{\text{market}} = 3.00$). There was a significant effect for *manipulation* ($F(4, 440) = 16.01$, $p < 0.001$, partial $\omega^2 = 0.12$), and there was also a significant interaction between *institution* and

Figure 2. (Color online) Average Number of Votes for Applicant B by Institution and Manipulation (Study 1)

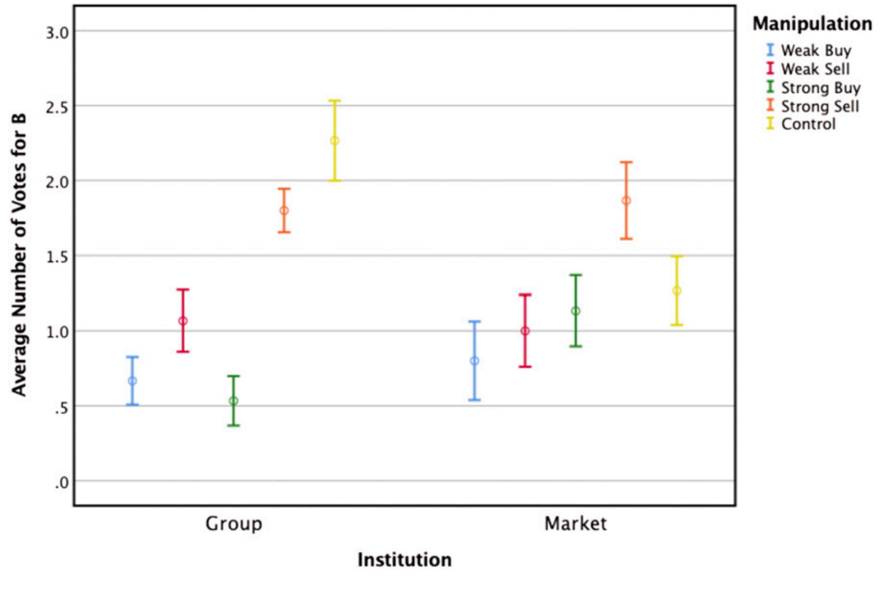


Table 3. Number of Groups with Perfect Solutions (All Three Participants Selected B, Study 1)

	Conditions		
Institutions	Control	Manipulation	Total
Groups	8/15	1/60	9/75
Market	1/15	8/60	9/75
Total	9/30	9/120	18/150

manipulation ($F(4, 440) = 11.50$, $p < 0.001$, partial $\omega^2 = 0.09$). Overall, and in most conditions, people trusted groups more than markets. There were two exceptions to this generalization that drove the interaction: (1) there was no difference in the trust in the two institutions in the control case, and (2) people trusted markets more than groups under the strong buy manipulation. Figure 3 provides a graphical depiction of the interaction.

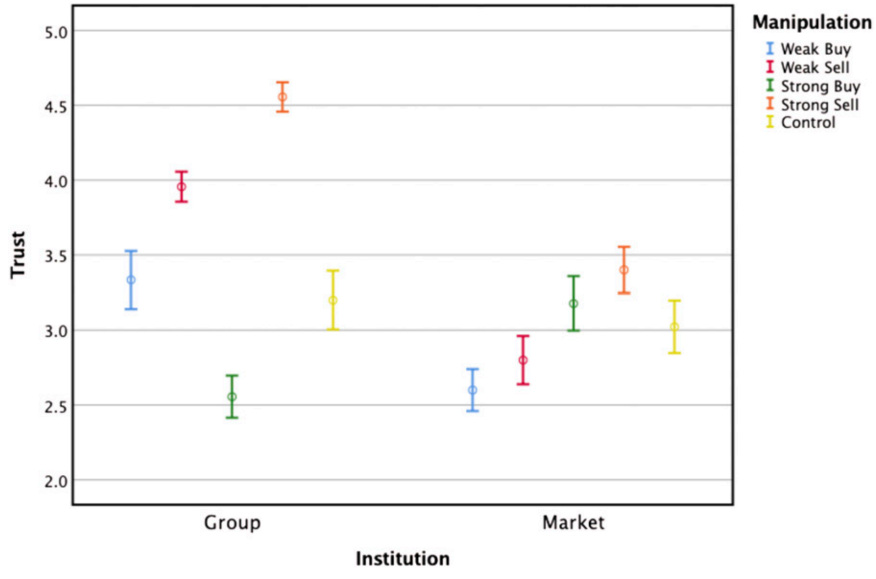
Discussion. The findings showed that groups outperformed markets in the absence of explicit manipulation attempts that induce conflicts of interest between the three members. However, in the presence of conflicts between the members/traders, induced by strong manipulation attempts, the picture flipped and markets performed significantly better than groups in uncovering the objectively best applicant. These findings are consistent with the findings of Lam and Schaubroeck (2000), who showed that participants in a team decision support system outperformed participants who interacted face to face when given conflicting information in a hidden-profiles task. Our market shares some of the characteristics of decision support systems (e.g., anonymity, structured information exchange) and also produced its best outcomes when conflicts were highest.

We also showed that people had more trust in the ability of groups to accurately aggregate the necessary information to identify the best candidate in most cases. The trust in markets was quite homogeneous under all manipulations, but we observed more variability in people's trust in groups. The trust in groups dipped below the markets only when everyone knew that there were side incentives to convince others to buy (be in favor) of one of the candidates.

Most importantly, the trust ratings showed that participants did not accurately anticipate the market's superior ability to uncover the objectively best candidate, in the presence of explicit manipulations. When regressing mean group trust, the actual proportion of correct selection was not significant, above the design variables (institution and manipulation).

In the next study, we sought to confirm these findings, and to understand why people generally have more trust in groups than in markets. One explanation is that this pattern reflects people's subjective perceptions of their experiences in their market/group and their earnings. To eliminate this possibility, we used a design involving observers of, rather than participants in, these institutions (who had no personal experience with them). We also tested the generalizability of our results by contrasting the hidden-profiles task with a hiring situation with a prediction task based on a market launch situation. We used a market launch scenario for the prediction task because prior work has shown the success of markets for that domain (Chen and Plott 2002, Dahan et al. 2011), whereas such demonstration has not yet been available for real-world hiring tasks.

Figure 3. (Color online) Average Trust by Institution and Manipulation (Study 1)



Study 2

Participants. Two hundred twenty-four participants (73 females, $M_{\text{age}} = 36.30$, $SD_{\text{age}} = 9.33$) recruited from Amazon Mechanical Turk took part in an online study, lasting between 10 and 15 minutes. Participants were paid $4.

Experimental Design and Procedure. Participants were randomly assigned to one of eight between-subjects conditions with the factors *interaction setting* (group discussion/market interaction), *conflicts of interest* (yes/no), and *task* (hidden profiles/prediction). In the group discussion setting, participants in the hidden profiles (prediction) condition were told that they would be watching a short video clip of a search (new product development) committee in which three potential candidates (products) (A, B, C) for a managerial position (market launch) are discussed. The video showed a group discussion of three participants (shot from behind without revealing the discussants' faces).[3] In the market-interaction setting, participants in the hidden profiles (prediction) condition were shown the screen of an information market where the shares traded corresponded to potential candidates (products) (A, B, C) for a managerial position (market launch). Participants were told that by observing market activity, such as the number and size of buying and selling offers and transactions, they would be able to draw inferences about the relative merits of the candidates (products). The videos showed a trading screen of a computerized double auction with voice-over-recording describing the actions.[4]

We also manipulated conflicts of interest. Half of the participants received information prior to the video informing them that, at least, one (unidentified) person in the group (market) had received private monetary incentives to affect the group discussion (market interaction) by convincing the others of the merits of one of the candidates (products), who (which) might not necessarily be the best suited candidate (product) for the position (market). The other half of the participants did not receive any information regarding potential conflicts of interest.

After watching the video, participants were asked to evaluate the interaction (group or market) with respect to a number of attributes that were extracted from the literature on organizational trust (Mayer et al. 1995, Adler 2001, Ba and Pavlou 2002, Gefen and Straub 2004, Tan et al. 2008). Specifically, participants evaluated groups and markets based on eight attributes: transparency, benevolence, efficiency, familiarity, fairness, integrity, predictability, and how natural they perceived them. Each item was answered on a seven-point Likert scale, ranging from 1 = strongly disagree to 7 = strongly agree.

Results. The responses to the eight attributes were highly correlated, suggesting the existence of a general trust factor. Hence, for the purpose of our analysis, we computed a composite measure of trust by averaging the eight items for each participant. We used this measure of trust as the dependent variable for a 2 (*interaction setting*: group vs. market) × 2 (*conflicts of interest*: yes vs. no) × 2 (*task*: hidden profiles vs. prediction) between-subjects ANOVA. The results indicate a significant main effect for *interaction setting* ($F(1, 216) = 51.14$, $p < 0.001$, $\eta^2 = 0.19$). People generally had more trust in groups than in markets (M_{group}=4.95, SD_{group}=0.83, M_{market}=4.03, SD_{market}=1.10). No other factor or interaction was statistically significant. Figure 4 displays the means and standard deviations for all eight trust attributes by interaction setting. The perceived superiority of the groups is confirmed for seven of the attributes ($p < 0.05$). The only exception is the attribute efficiency, where there was no difference between the two settings.

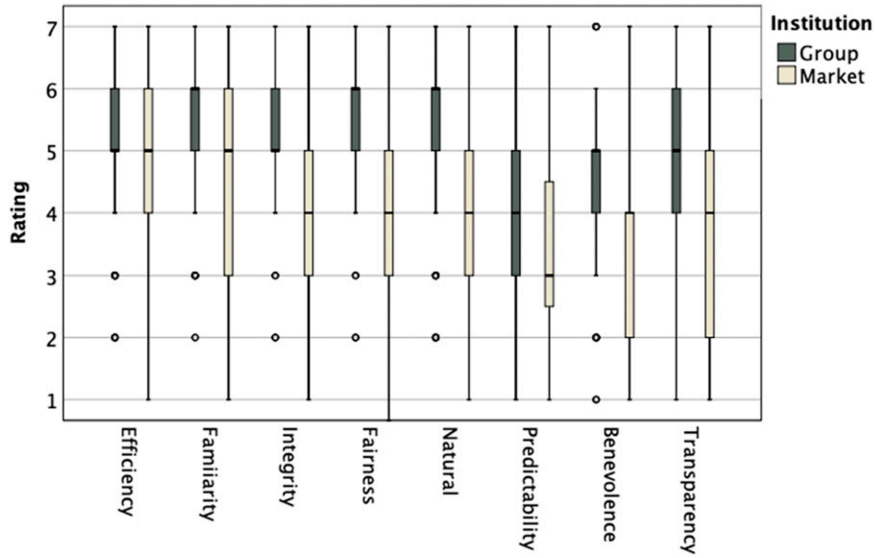
Discussion. We confirmed a key finding from Study 1. People placed higher trust in groups than in markets. In this study, the participants were purely observers and did not take part in the group deliberations or market trading. Thus, participants' trust judgments cannot be attributed to personal experience, and we can conclude that they represented general perceptions of the two institutions. Moreover, participants were not sensitive to conflicts of interest. Neither in the group nor in the market setting did participants reduce their trust in the institutions when manipulation attempts were present. The results were also not qualified by the task, suggesting that the hidden-profiles paradigm generalizes well to other tasks, such as the simple prediction framework considered in this study.

In the next study, we sought to better understand why people placed higher trust in groups than in markets, by asking participants to observe both institutions and to evaluate them in a comparative fashion. We also sought to examine whether experience and familiarity with markets increases trust by studying experienced forecasters from the Good Judgment Forecasting project.[5]

Study 3

Participants. In this online study, lasting between 10 and 15 minutes, we recruited 358 participants (69 females, $M_{\text{age}} = 46.56$, $SD_{\text{age}} = 13.25$) from the Good Judgment Open forecasting project. Good Judgment Open is owned and operated by Good Judgment, a forecasting services firm that provides corporate and government decision makers with crowd-sourced forecasting data.

Figure 4. (Color online) Trust Attributes by Institution (Study 2)



Experimental Design and Procedure. Participants were told that they would be heading a search committee to select one of three candidates (A, B, C) for a managerial position. Participants were told to decide whether they would like their search team to operate as a committee or as a market. In the committee, all members received information about the candidates and then interacted with the other members face to face. In the market, all members held shares representing the candidates and traded them and sought to buy shares of the candidates they favored and to sell shares of the candidates they did not like. Afterward, participants were shown two 30-seconds video clips depicting (i) a group discussion (committee) of three participants (shot from behind without revealing the discussants' faces) and (ii) the screen of a computerized double auction (market) with voiceover recording describing the actions.[6] In both cases, information about the job applicants was exchanged. The order of presentation of the two video clips was counter-balanced, such that half of the participants first saw the committee and then the market, and the other half saw them in the opposite order. After watching the videos, participants were asked which of the two settings (committee or market) they wished to join as the head of the search committee.

Then, we asked participants to evaluate the two institutions (committees and markets) comparatively with respect to the various attributes used in Study 2: transparency, benevolence, efficiency, familiarity, fairness, integrity, predictability, and how natural they perceived the two institutions. Since we asked participants to evaluate committees directly with markets, we also asked them to indicate which one was better. We used seven-point Likert scales of the following format: "Which of the two settings is more ATTRIBUTE?" (with committees = 1, markets = 7, and 4 as a neutral anchor).

Finally, we asked participants how long they had been active on the forecasting project, how many events they had forecasted so far, and whether they had previously participated in the Good Judgment Forecasting Tournament. If they participated in the original tournament, we also asked them whether they participated as individuals, as part of teams, or as part of prediction markets. Participants could have been active in more than one forecasting format. Finally, we asked them whether they had any experience with prediction markets (even outside the tournament), and if so, in what capacity.

Results. We tested whether the ratings of the committees and markets on the nine attributes differed significantly from the midpoint (i.e., 4) of the scales. Participants perceived committees to be relatively more benevolent (mean = −0.51; $t(356) = -5.65$, $p < 0.001$), natural (mean = −1.66; $t(356) = -18.92$, $p < 0.001$), familiar (mean = −2.11; $t(356) = -28.76$, $p < 0.001$), and better (mean = −0.22; $t(356) = -2.21$, $p = 0.028$) than markets. On the other hand, participants perceived markets to be relatively more efficient (mean = 0.99; $t(356) = 10.37$, $p < 0.001$) and fairer (mean = 0.30; $t(355) = 3.32$, $p < 0.001$) than committees.

To test our hypothesis that prior experience with markets would improve their assessments, we ran a multivariate analysis of variance (MANOVA) with the nine comparative assessment statements as dependent variables and prior experience with different prediction settings as the independent variable. Specifically, we contrasted participants who took part in the Good Judgment Forecasting Tournament as part of teams and as individuals (n = 174), those who participated as part of markets and as individuals (n = 54), and those who did not take part in the forecasting tournament (n = 107). Since participants varied in terms of their forecasting experience, ranging from 0 to 72 months, we also included their forecasting experience as a covariate. The results reveal a significant main effect for *prior experience* with different prediction settings (Wilks' $\Lambda = 0.95$, $F(18, 646) = 1.63$, $p = 0.048$, $\eta^2 = 0.04$), but no significant effect for *forecasting experience*. Univariate tests indicate that assessments differed significantly for the attributes of benevolence ($F(2, 331) = 5.08$, $p = 0.007$, $\eta^2 = 0.03$), integrity ($F(2, 331) = 4.08$, $p = 0.018$, $\eta^2 = 0.02$), efficiency ($F(2, 331) = 3.45$, $p = 0.033$, $\eta^2 = 0.02$), fairness ($F(2, 331) = 5.97$, $p = 0.003$, $\eta^2 = 0.04$), as well as for better ($F(2, 331) = 6.38$, $p = 0.002$, $\eta^2 = 0.04$) and natural ($F(2, 331) = 3.15$, $p = 0.044$, $\eta^2 = 0.02$). Bonferroni posthoc tests indicated that the differences were driven by the contrast between participants with prior forecasting experience as part of teams and as individuals versus participants who did not take part in the forecasting tournament. Participants in the latter category generally provided higher evaluations of markets than the former group with respect to benevolence ($p = 0.006$), integrity ($p = 0.015$), efficiency ($p = 0.027$), fairness ($p = 0.003$), and also found them to be better overall ($p = 0.001$). Participants with prior experience in markets and as individuals fell in between these extremes.

To test more directly our prediction that prior experience with markets would increase the trust that people have in the predictive abilities of markets, we analyzed the choices of those participants who previously took part in the Good Judgment Forecasting Tournament as part of singular settings only (excluding those who took part in multiple forecasting settings, such as individuals and as part of teams). This resulted in a sample size of 150 participants, out of which 116 took part in the tournament as individual forecasters, 25 took part exclusively in team forecasting, and the remaining nine participants took part in market forecasting. We analyzed their choices to the question of which setting, committee or market, they would prefer for the assessment of job candidates. The participants differed significantly across the three groups ($\chi^2(2) = 10.83$, $p = 0.004$). Whereas participants who took part in the forecasting tournament as individuals or as part of teams generally preferred committees over markets, those participants who took part in markets expressed the opposite preference (see Table 4).

Table 4. Preference for Setting by Participant's Forecasting Experience (Study 3)

	Prior exclusive forecasting experience			
Preference for	Individuals	Teams	Markets	Total
Committees	92	21	3	116
Markets	24	4	6	34
Total	116	25	9	150

Discussion. The findings showed that there was a halo effect, as people reported higher levels of trust for the more familiar institution, namely for committees as compared with markets. In general, people were much more familiar with group settings than with markets. We suspect that they relied on this familiarity when evaluating aggregation settings—without considering the possibility that some members follow private motives, which are incompatible with the aggregation goal. The implication is that individuals are often too credulous. Markets, on the other hand, which were evaluated as less natural, benevolent, familiar, and worse than group settings, were less popular, with fewer people wishing to join them. However, if people had concrete experience with markets, this preference flipped, and they preferred markets over committees.

General Discussion

We showed that groups outperformed markets in the absence of explicit manipulations; however, in the presence of conflicts between members/traders, markets performed significantly better than groups. Yet, people had more trust in the ability of groups to accurately aggregate information, irrespective of the existence or absence of explicit manipulation attempts. Overall, people evaluated groups more favorably than markets because they were perceived to be more natural and familiar and better at solving the problem, and showed higher benevolence. However, participants who had previous relevant experience with markets favored markets over groups (committees).

Despite the markets' strong performance, particularly under adverse conditions induced by the manipulation attempts, there are certain limitations in their implementation (Croxson 2011). Markets can only be implemented if the event or problem of interest can be defined unambiguously and if a contract can be stipulated that contains a small number of mutually exclusive events or outcomes. Operationally, it is equally important to have a sufficiently "thick" market, that is, one that includes a large number of active traders. However, Healy et al. (2010, study 1) showed that even a market with three traders performs relatively well given that the problem is simple enough and involves binary (true-false) events. This approach can be easily extended. If an organization wanted to predict a continuous variable, such as future sales, it could partition the possible range into a manageable (say 7 ± 2) number of bins and specify the prediction horizon. The winning range (one that includes the eventual sales at the closing time) would pay a dollar prize, whereas the other ranges would not pay anything.

Another limitation of markets, which is the main topic of this work, is the surprisingly low trust that people seem to place in their performance. These limitations do not seem to be major obstacles in many applications, such as forecasting future geopolitical events across a variety of different domains (e.g., Atanasov et al. 2017). Tackling the lack of trust in markets might be alleviated by having people participate in practice markets. Evidence from the Good Judgment Forecasting Tournament (Good Judgment Project 2015) indicates that when given a choice, the majority of participants in the market condition expressed a wish to switch to the team condition; however, eventual satisfaction and motivation with the market did not differ significantly from the team condition. This suggests that experiencing the market first-hand might reduce the desire to switch.

In general, markets have some clear advantages over teams and committees in organizational settings: (1) Markets can be (and typically are) anonymous, so they provide opportunities for people in lower (or otherwise vulnerable) positions in the organization to contribute without any fears or inhibitions; (2) markets can accommodate larger numbers of participants than typical committees, teams, or focus groups, and as such involve more diverse opinions and estimates; (3) markets are flexible and they can be active for longer than typical committees or group meetings, and allow for new traders to join and for new information to be added throughout the market duration; and (4) markets are less influenced by external manipulation attempts and, hence, may provide more reliable signals to management than teams and committees.

Although the markets' relative robustness to manipulation attempts has been well documented in the literature (e.g., Camerer 1998, Jiang et al. 2005, Hanson et al. 2006, Hanson and Oprea 2009, Berg and Rietz 2014), they are not totally immune to manipulation (e.g., Veiga and Vorsatz 2009, 2010; Deck et al. 2013), and the exact conditions under which markets perform well are still a focus for future research. Our work suggests that for relatively simple problems with an intellective solution that can be expressed by clear true/false statements and with a sufficient number of traders (Healy et al. 2010), markets are more robust against manipulation than comparable group settings. Our results are fairly general, as we chose the minimal number of traders reported in the literature for the markets to still perform well (Healy et al. 2010). Thicker markets, with more traders, should perform even better. For groups, many studies point to the potential negative effects of an increase in group size on performance, due to coordination difficulties and motivational loss (e.g., Steiner 1972). Our group size of three participants showed that performance is strong, as 13 out of 15 groups in the control condition uncovered the best candidate, inferred by majority rule. However, with the introduction of conflicts of interest our results switched, and markets outperformed groups. These combined effects suggest that the mean difference between markets and groups becomes even more pronounced as the number of members increases; however, the uncovered interaction effect likely maintains.

One reason why people might trust markets less than groups is algorithm aversion. Although algorithms outperform human forecasters, people consistently choose to rely on human forecasts as decision inputs rather than relying on algorithms (Dietvorst et al. 2015). The main reason for this preference is that people lose confidence in algorithms after seeing them make the same mistakes as human forecasters. This holds true for simple algorithms, like averaging (Larrick and Soll 2006). Recently, Kaufmann and Budescu (2019) showed that teachers prefer to obtain advice from school counselors rather than computerized systems. The teachers consistently rated the counselors as more reliable, accurate, transparent, and trustworthy. Our findings complement these results, as markets were perceived to be less natural and familiar than groups (just like algorithms are less transparent than human judges).

People not only have less confidence and trust in nontransparent mechanisms, like algorithms and markets, they also have difficulty in identifying, and correcting for, conflicts of interest (see the review by Bonaccio and Dalal 2006). The literature showed that even though decision makers knew the direction and magnitude of the biased advice, they failed to adequately correct for this bias in their judgments (Cain et al. 2005, 2011). Paradoxically, when conflicts of interest were disclosed, advisors felt comfortable giving even more biased recommendations and judges felt more pressure to comply with the advice (Loewenstein et al. 2011). This effect was further exacerbated in the presence of secondary advice. In these cases, primary advisors provided even more biased recommendations (Sah and Loewenstein 2015). Our work complements these findings by showing that conflicts of interest also have a profound negative effect on group decisions and, more importantly, demonstrate that these effects can be avoided. Markets with identical information and identical number of participants outperformed the group setting under adverse conditions.

One of our initial questions focused on why organizations show relatively limited enthusiasm to implement information markets despite the market's success in pooling and aggregating information. Our findings suggest that the main reason for the limited trust that people have in markets is their relative unfamiliarity and the perceived lack of benevolence. "Group-level differences in economic organization and the structure of social interactions explain a substantial portion of the behavioral variation across societies: The higher the degree of market integration and the higher the payoffs to cooperation in everyday life, the greater the level of prosociality expressed in experimental games" (Heinrich et al. 2005, p. 795). Our results are consistent with the findings from small-scale communities around the world. It appears that the more frequently people engage in market exchanges, the higher the level of trust in markets.

Limitations and Future Directions

Despite our strong results, it is important to point out that we only studied one type of market (a fairly thinly populated double auction with three participants), only one type of group setting (a face-to-face interaction with free communication and three participants), and one type of decision problem (a hidden-profiles task with asymmetric information and symmetric influence). Future research is needed to investigate the generality of these results and determine for what type of problems the findings will be replicated, for what type of market and group settings, and for what interaction sizes. Hidden profiles capture some organizational problems, but certainly not all. Many settings involve asymmetric influence and power differentials (e.g., hierarchical and parallel group structures) that may lead to different findings (e.g., Knudsen et al. 2018, Navajas et al. 2018) and these are potential settings for future study.

Similarly, the repeated nature of interactions in organizations, and the resulting reputation effects, might impact how comfortable people are to withhold information from their coworkers. The level of scrutiny that is involved in studying market signals, and potentially engaging in correcting these signals by exploiting inefficiencies (by arbitrage), might also vary in organizations and might be a function of task importance and ease of information processing, among other factors. Also, trust in markets might be more an issue in thinner markets with less scrutiny (e.g., real estate markets) than in thicker stock markets that are heavily scrutinized and are instantaneously accessible worldwide.

Future research should also investigate whether allowing for group decision making in markets would improve the perceived benevolence of markets and lead people to place higher trust in them. Recent evidence suggests that such intrateam collaboration improves performance of markets (Maciejovsky et al. 2013) and might also narrow the gap between prediction markets and prediction polls (Atanasov et al. 2017). Another avenue is to investigate why organizations rely on group processes to such a high degree. One reason is that organizations are aware of the shortfalls of groups in terms of accuracy, but groups might serve other purposes (Sutton and Hargadon 1996), for example, supporting organizational memory or increasing involvement and identification with the organization.

It would also be interesting to study the impact of diversity (Woolley et al. 2015), task domain (e.g., prediction vs. discovery), and organizational structure on aggregation (Christensen and Knudsen 2010, Csaszar and Eggers 2013) by, for instance, allowing for decision makers to be clustered and for the presence of influence patterns (Puranam and Maciejovsky 2017). Finally, it would be interesting to compare markets with other forms of computer-mediated interactions to investigate whether people display similar levels of trust in these settings compared with face-to-face groups, and how trust in these settings could be improved (e.g., de Melo et al. 2013).

Acknowledgment

The authors thank the Good Judgment Project for allowing them access to their forecasters.

Endnotes

[1] In accordance with the literature (Wolfers and Zitzewitz 2004), we use the terms "prediction markets" and "information markets" interchangeably.

[2] The data for all three studies can be found in the online appendix to this article. All measures, conditions, and instances of data exclusions are reported in the article.

[3] The group discussion video for the hidden profiles task can be seen at https://www.youtube.com/watch?v=Aw46yFPoW9Q&feature=youtu.be and the one for the prediction task at https://www.youtube.com/watch?v=rNMt3u8OEPU&feature=youtu.be.

[4] The market interaction video for the hidden profiles task can be seen at https://www.youtube.com/watch?v=cbUZCH4RUnU&feature=youtu.be and the one for the prediction task at https://www.youtube.com/watch?v=jOaEXqm3y44&feature=youtu.be.

[5] See https://www.gjopen.com/.

[6] The group (committee) discussion video can be seen at http://www.youtube.com/watch?v=irX_jwgWKCk and the one for the market at http://www.youtube.com/watch?v=HDeoxn2eGE8.

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Boris Maciejovsky is an associate professor of management in the School of Business at the University of California, Riverside. He received his doctoral degree from the University of Vienna and his PhD from the Massachusetts Institute of Technology. His research interests include group decision making, learning, and knowledge transfer as well as information aggregation and negotiation.

David V. Budescu is the Anne Anastasi Professor of Psychometrics and Quantitative Psychology at Fordham University. He received his PhD from the University of North Carolina, Chapel Hill, and his research is in the areas of human judgment, individual and group decision making under uncertainty and with incomplete and vague information, information aggregation and methodology, and statistics for the behavioral and social sciences. He is the editor of *Decision*, and past associate editor of *Decision Analysis* and *Psychological Methods*.