



Network dynamics of social influence in the wisdom of crowds

Joshua Becker^a, Devon Brackbill^a, and Damon Centola^{a,b,1}

^aAnnenberg School for Communication, University of Pennsylvania, Philadelphia, PA 19104; and ^bSchool of Engineering, University of Pennsylvania, Philadelphia, PA 19104

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A longstanding problem in the social, biological, and computational sciences is to determine how groups of distributed individuals can form intelligent collective judgments. Since Galton's discovery of the "wisdom of crowds" [Galton F (1907) *Nature* 75:450–451], theories of collective intelligence have suggested that the accuracy of group judgments requires individuals to be either independent, with uncorrelated beliefs, or diverse, with negatively correlated beliefs [Page S (2008) *The Difference: How the Power of Diversity Creates Better Groups, Firms, Schools, and Societies*]. Previous experimental studies have supported this view by arguing that social influence undermines the wisdom of crowds. These results showed that individuals' estimates became more similar when subjects observed each other's beliefs, thereby reducing diversity without a corresponding increase in group accuracy [Lorenz J, Rauhut H, Schweitzer F, Helbing D (2011) *Proc Natl Acad Sci USA* 108:9020–9025]. By contrast, we show general network conditions under which social influence improves the accuracy of group estimates, even as individual beliefs become more similar. We present theoretical predictions and experimental results showing that, in decentralized communication networks, group estimates become reliably more accurate as a result of information exchange. We further show that the dynamics of group accuracy change with network structure. In centralized networks, where the influence of central individuals dominates the collective estimation process, group estimates become more likely to increase in error.

social networks | collective intelligence | social learning | wisdom of crowds | experimental social science

Since Galton's discovery of the "wisdom of crowds" over 100 years ago (1), results on crowdsourcing (1, 2), prediction markets (3), and financial forecasting (4, 5) have shown that the aggregated judgment of many individuals can be more accurate than the judgments of individual experts (2, 4, 6–8). Statistical explanations for this phenomenon argue that group accuracy relies on estimates taken from groups where individuals' errors are either uncorrelated or negatively correlated, thereby preserving the diversity of opinions in a population (9). Thus, although individuals may have estimates both far above and far below the true value, in aggregate these errors cancel out, leaving an accurate group judgment (2, 9, 10).

Recent experimental evidence has suggested that the wisdom of crowds may be undermined by processes of social influence, in which people exchange information about their estimates and revise their judgments to align with one another (11–13). When social influence leads to correlated errors, both independence and diversity are reduced, which has been argued to compromise the reliability of the group judgment (9, 11–18). In direct contrast with these results, however, theoretical models of social learning (19–21) have suggested that the effects of social influence on collective decisions vary based on the structure of the interaction network, predicting that, under the right conditions, social learning can lead a group's median judgment to improve (20–24).

This prediction derives from the assumption that, when people learn about the beliefs of others, they revise their own beliefs to become more similar to their social referents (11, 12, 25, 26).

Following the DeGroot model of social learning, this theory suggests that each individual's revisions are based on a weighted average of their own belief and the beliefs of their social referents (19). Thus, an individual's revision is determined in part by the amount of weight they place on their own belief relative to social information. When this "self-weight" is independently and identically distributed (i.i.d.) throughout a population, and the population is embedded in a decentralized social network (i.e., one in which everyone is equally connected), this model predicts that belief distributions will converge on the statistical mean of the initial, independent beliefs (*SI Appendix*). Thus, if the initial group mean is accurate, exposure to social influence will lead individuals in the group to become more accurate, improving the accuracy of the group's median, even as the group mean remains fixed (*SI Appendix*).

We build on the DeGroot model to generate theoretical predictions for how social influence can affect the accuracy of group judgments. We show that if individuals' self-weights are not i.i.d. in the population, but are instead correlated with individual accuracy, then social influence may not only improve the median judgment by bringing it toward the mean, but may also result in the mean of the population estimate becoming more accurate. This prediction builds on the DeMarzo et al. (20) notion of social influence weight, which identifies the amount of influence that each individual in a network has on the collective belief. Because self-weight contributes to social influence weight, a correlation between accuracy and self-weight means that more accurate individuals will be more influential in the group estimate, resulting in a direct improvement in the accuracy of the group mean.

Our predictions also show that this process can go awry if some individuals in a population are more prominent than others,

Significance

Since the discovery of the wisdom of crowds over 100 years ago theories of collective intelligence have held that group accuracy requires either statistical independence or informational diversity among individual beliefs. Empirical evidence suggests that allowing people to observe the beliefs of others leads to increased similarity of individual estimates, reducing independence and diversity without a corresponding increase in group accuracy. As a result, social influence is expected to undermine the wisdom of crowds. We present theoretical predictions and experimental findings demonstrating that, in decentralized networks, social influence generates learning dynamics that reliably improve the wisdom of crowds. We identify general conditions under which influence, not independence, produces the most accurate group judgments.

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¹To whom correspondence should be addressed. Email: dcentola@asc.upenn.edu.

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giving them disproportionate levels of social influence in the population. Theoretical results suggest that when networks are highly “centralized” in this way, instead of efficiently aggregating all available information, populations are biased toward the beliefs of the central individuals (20), which can significantly influence the accuracy of the collective judgment (*SI Appendix*). This effect of centralization on group estimates has been predicted by a variety of social learning models, including both fixed (20, 23) and growing (21, 24) networks, as well as models of both discrete choice (23, 24) and continuous estimation (20, 21).

We test these theoretical predictions using a web-based experimental design (27, 28). We recruited subjects to participate in a series of large-group estimation tasks and compared the effects of social influence in both centralized and decentralized networks to a control condition in which there was no social influence. Consistent with previous work, our theoretical results predict that centralized networks will exhibit a bias toward the beliefs of central individuals. However, in contrast to prior work showing that social influence undermines group accuracy (11–18), we predict that social influence in decentralized networks will improve the accuracy of the group median (*SI Appendix*). Moreover, we also predict that social influence can produce systematic improvements in the accuracy of the group mean if the individual revision process is not i.i.d., but is correlated with individual accuracy. As described below, our experimental design permits a direct test of these theoretical predictions based on our extensions of the DeGroot model.

Theoretical Model. We build on DeGroot’s (19) formalization of local information aggregation, in which subject i updates their response estimate, $R_{t,i}$, after being exposed to the estimates of their network neighbors, $\bar{R}_{t,j \in N_i}$. We define a subject’s revision process with three components: their own estimate; the estimates of network neighbors; and self-weight or the amount of weight they place on their own estimate relative to the estimates of their network neighbors. In this model, each subject responds to social information by adopting a weighted mean of their own estimate and the estimates of their neighbors, according to the rule:

$$R_{t+1,i} = \alpha_i \times R_{t,i} + (1 - \alpha_i) \times \bar{R}_{t,j \in N_i},$$

where the value $R_{t,i}$ indicates the response of subject i at time t ; α_i indicates the self-weight a subject places on their own initial estimate; $(1 - \alpha_i)$ indicates the weight they place on the average estimate of their network neighbors; and $\bar{R}_{t,j \in N_i}$ indicates the average estimate of subject i ’s network neighbors at time t . Outcomes are therefore determined by three parameters: the communication network (i.e., who can observe whom); the distribution of initial estimates, R_1 ; and the distribution of self-weights, α_i .

At the population level, this model states that the group estimate after t revisions can be calculated as a function of a weighted, directed network of social influence (19). In this social influence network, a tie exists from node i to node j if i can observe j in the communication network. The tie has a numeric value that indicates the weight that node i places on the estimate of node j , which is determined by α_i . For any given node i , the sum of the outgoing tie weights equals $(1 - \alpha_i)$. Consistent with previous implementations of this model (19–21), we represent the self-weight that node i places on its own estimate (α_i) as a “self-tie” from i to i . The set of each node’s outgoing tie weights (including their self-tie) sums to 1. The sum of each node’s incoming ties (including their self-tie) is proportional to their overall influence in the network during each round of revisions—i.e., their “social influence weight,” which is defined as each subject’s influence in the collective estimation process (20). Because this sum includes the subject’s

self-weight, each subject’s influence in the collective estimation process is determined in part by how heavily they weight their own opinion compared with the social information they receive.

This concept of social influence weight comes from the properties of the DeGroot model, in which members of a population revise their estimates indefinitely according to the process above. Through this revision process, the DeGroot model predicts that, in a wide range of network structures, all members of the population will asymptotically converge on a single shared estimate (19). The collective estimate after social influence is a weighted mean of the initial independent estimates (20). Each individual’s social influence weight is defined by the size of the contribution that their initial (independent) estimate makes to the final collective estimate (20). The relationship between self-weight and social influence weight reflects the fact that when a subject places more weight on their own individual belief, they adjust their belief less in response to others, and thereby contribute more weight to the group estimate (20).

In decentralized networks—defined as networks where everyone has the same number of ties (29)—the properties of the model described above indicate that the arithmetic mean of a group’s estimate distribution will remain unchanged, even as social influence leads individuals’ estimates to become more similar. This prediction (convergence toward the mean) holds under the assumption that self-weight is i.i.d. throughout a population (*SI Appendix*). If this process accurately characterizes the effects of influence on the wisdom of crowds, and the initial group mean is accurate, then social influence in decentralized networks allows individuals to increase the accuracy of their estimates without any deleterious effects on group-level accuracy. One consequence of this process is that the median of the group estimate can improve, while the mean stays fixed (*SI Appendix*).

We extend these predictions by analyzing what happens when this i.i.d. assumption is violated—i.e., there is non-i.i.d. heterogeneity in the degree to which individuals revise their estimates based on the estimates of others. Our results predict that if an individual’s self-weight is correlated with their accuracy, social influence dynamics may not only be able to improve the median judgment by bringing it toward the mean, but may also result in the mean of the population estimate becoming more accurate as a function of social influence (*SI Appendix*).

Experimental Design. We recruited 1,360 participants from the World Wide Web to take part in a series of estimation challenges. Subjects were randomized either to one of two experimental social network conditions or to a control condition. In all conditions, participants were prompted to complete estimation tasks and were awarded a monetary prize based on the accuracy of their final estimate. In the network conditions, participants were placed into either a decentralized network, in which everyone had equal connectivity, or a centralized network, in which a highly connected central member had a disproportionate number of connections (*Materials and Methods* and *SI Appendix*, Figs. S1 and S7).

Each social network contained 40 subjects. Within each network, all subjects were simultaneously shown the same image prompt (e.g., a plate of food) and asked to estimate a numerical quantity (e.g., the caloric content) (*SI Appendix*). There were three rounds for each estimation task. In round 1, participants provided an independent estimate based on the prompt. In both network conditions, participants were then shown the average estimate of the peers directly connected to them in their social network and prompted to submit their answers again in round 2. Subjects were then shown the average of their peers’ revised estimates and prompted to submit a final estimate in round 3. Thus, for each question, participants provided one independent

estimate and two estimates after exposure to social information, for a total of three estimates per question. Subjects were not provided with any information about their social networks, which ensured that the subject experience was identical across the two network conditions.

Subjects who were randomized to the control condition were not placed into social networks, but were instead given the opportunity to answer the same questions without being exposed to social influence. These participants were still given the opportunity to revise their initial answer two times, providing a total of three independent estimates per question. All control participants observed the same sets of questions in the same order as participants embedded within the experimental networks. More generally, the subject experience in the control condition was identical to that of subjects in other conditions, except that participants were not given any social information.

Each experimental trial of the study consisted of an identical set of questions provided to one decentralized network (40 individuals) and one centralized network (40 individuals). For each set of questions that was asked in the experimental trials, we also collected responses from 40 independent individuals in the control condition, who collectively formed a “control group” for that set of questions. Each subject participated only once in our study—either in one network condition or in one control group—such that every network condition and control group comprised a unique set of 40 individuals.

Because subjects in the network conditions were not statistically independent, all analyses of collective estimates in the network conditions were conducted at the group level (*SI Appendix*). Moreover, because each network completed multiple estimation tasks within an experimental trial, we cluster our main analysis at the trial level such that each network provided a single, independent observation (*SI Appendix*). In total, we conducted 13 experimental trials, comprising 520 subjects in each network condition (1,040 experimental subjects in total). In six of the experimental trials, subjects answered four questions in each trial, where each question set was unique. In the remaining seven trials, subjects answered five questions in each trial, using two unique questions over repeated trials. In total, this process produced eight unique question sets.

Control groups were conducted corresponding to each unique question set, producing eight control groups, each of size 40 (320 control subjects in total) (*Materials and Methods*). Because subjects in the control groups were independent from each other, fewer overall subjects were required for the control analyses (*Materials and Methods* and *SI Appendix*). Nevertheless, for proper comparison with the experimental conditions, we still conducted our control trials with subjects in groups of 40 and conducted our analyses at the group level (*SI Appendix*).

We measured the cumulative effect of social influence on collective judgments by comparing the initial estimates of each group (i.e., in round 1 of our study), with the final estimates of each group after two rounds of revision (i.e., in round 3). For results where we report percent change, all comparisons were made between final estimates (i.e., round 3) and independent estimates (i.e., round 1), so that percent change was measured as the magnitude of the change in the estimate divided by the magnitude of the initial estimate (*SI Appendix*). To facilitate comparisons across different estimation tasks of different scales (i.e., some questions have true answers $>1,000$, whereas some questions have true answers <100), we normalized all estimates, dividing them by the standard deviation (SD) of the independent responses for each question (*SI Appendix*). All reported changes in error were therefore measured in terms of the distance of each estimate from the truth, represented as the number of SDs away from the true answer (comparable to a z-score).

Results

Social network structure significantly affected the wisdom of crowds. We found both that decentralized networks showed the predicted increase in collective accuracy and that centralized networks exhibited the predicted bias toward the beliefs of central individuals. We begin our analysis by confirming that in the independent round (i.e., round 1 of all trials), groups exhibited the wisdom of crowds. Consistent with earlier studies (1, 5–8, 13), we found that, on average, both the mean and the median of each group’s estimate was more accurate than the majority of its members (*SI Appendix*). In the results that follow, we analyze how social influence affected the trajectory of group estimates in each of the network conditions.

Decentralized Networks. Social influence dramatically reduced the diversity of group estimates. As shown in Fig. 1D, two rounds of revision significantly narrowed the SD of responses ($n = 13$ trials, $P < 0.001$, Wilcoxon signed rank test), producing a 43% reduction in the average SD between rounds 1 and 3. This sizeable reduction in diversity replicates the main finding from previous experimental research on social influence in the wisdom of crowds (13).

However, this reduction in diversity did not undermine the wisdom of crowds. Rather, consistent with previous research (30, 31), we found that social influence in decentralized networks

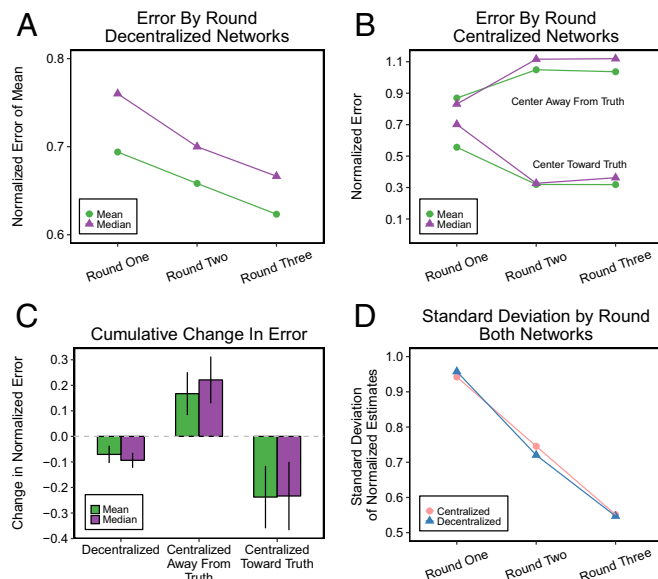


Fig. 1. Effect of social influence on group accuracy in centralized and decentralized networks. Average error and SD in 13 experimental trials for each network condition are shown. (A) In decentralized networks, both the mean and the median became more accurate over two rounds of social influence. (B) In centralized networks, the effect of social influence on the accuracy of the group mean and group median was determined by the initial estimate of the central node. Results were conditioned on whether the central node was in the direction of truth relative to the group estimate. (C) Total change from round 1 to round 3 with bootstrapped 95% error bars, indicating that changes shown in A and B are significant. Both the mean and median of estimates in decentralized networks became more accurate ($n = 13$, $P < 0.01$ for mean, $P < 0.001$ for median). For centralized networks, the mean and median became less accurate when the central node provided an estimate in the opposite direction of truth ($n = 13$, $P < 0.01$ for both mean and median). Both the mean and median became more accurate when the central node provided an estimate in the direction of truth ($n = 12$, $P < 0.01$ for the mean and median). (D) In both network conditions, the SD in the distribution of estimates (i.e., diversity of opinions) decreased significantly after each round of revision ($n = 13$, $P < 0.001$ for both conditions).

produced significant improvements in individual accuracy. Across all 13 trials with decentralized networks, average individual error was significantly lower in round 3 than it was in round 1, decreasing by 23% on average ($n = 13$ trials, $P < 0.001$, Wilcoxon signed rank test). In addition to these individual-level improvements, we also found that the average error of each group's median estimate was significantly lower in round 3 (0.67 SD) than in round 1 (0.76 SD) ($n = 13$ trials, $P < 0.001$, Wilcoxon signed rank test), resulting in a 12% decrease in average error, as shown in Fig. 1*A* and *C*.

In our analysis of how social influence produced these group-level improvements in the median, our initial expectation was that self-weights were i.i.d. within each network. On this assumption, the DeGroot (19) model predicts that social influence in decentralized networks can improve the group median by pushing it toward the mean of the group's independent estimate, which is not expected to change (*SI Appendix*). Remarkably, however, we found that, on average, each group's mean estimate also became more accurate. After two rounds of exposure to social influence, the average error of the group mean at round 3 (0.62 SD) was significantly lower than at round 1 (0.69 SD) ($n = 13$ trials, $P < 0.01$, Wilcoxon signed rank test), resulting in a 10% reduction in the average error of the group mean. These findings can be explained with the DeGroot model by observing that individuals' self-weights were not identically distributed in the population.

Fig. 2 shows that across all network conditions, the magnitude of an individual's revisions from round 1 to 3 was significantly correlated with the magnitude of their initial error ($n = 4,340$ estimates by 1,040 subjects, $\rho = 0.41$, 95% CI [0.39, 0.43], $P < 0.001$, analysis of covariance). Because each individual completed multiple estimation tasks, we measure this relationship between individual accuracy and revision magnitude after controlling for correlation between estimates by the same individual (*SI Appendix*). The results (Fig. 2) show that initially accurate individuals made smaller revisions to their estimates, whereas initially inaccurate individuals made larger revisions. Consistent with the DeGroot model, one explanation for this revision pattern is that individuals who were more accurate had greater self-weight in their revisions than individuals who were less accurate. This explanation is consistent with the observed behavior; however, our analysis also needs to account for the observation that individuals who were more accurate also had estimates that were closer to their observed neighborhood average. Consequently, the positive correlation between error and revision magnitude may be due to the fact that subjects whose initial estimates were farther from their neighborhood average were inclined to make larger revisions, rather than to the fact that more accurate individuals had a stronger self-weighting.

To control for this potentially confounding effect, we measured the partial correlation between error and revision magnitude, while holding constant the distance between the subject's initial estimate and the initial neighborhood estimate. *Inset* in Fig. 2 shows that, even with this statistical control, more accurate individuals still made smaller revisions to their estimates than less accurate individuals ($n = 4,340$ estimates by 1,040 subjects, $\rho = 0.25$, 95% CI [0.22, 0.28], $P < 0.001$, analysis of covariance). This result suggests that accurate individuals placed more weight on their own estimates and less weight on social information (*SI Appendix*). By contrast, less inaccurate individuals had a lower self-weight and were more influenced by social information. For clarity, we refer to this partial correlation between accuracy and self-weight as the revision coefficient.

As discussed above, each individual's social influence weight in the network is determined in part by their self-weight, so that individuals who place more weight on their own estimate are also more influential in the collective estimate. When considered in the context of our theoretical model, the correlation shown in Fig. 2 indicates that more accurate individuals had a larger

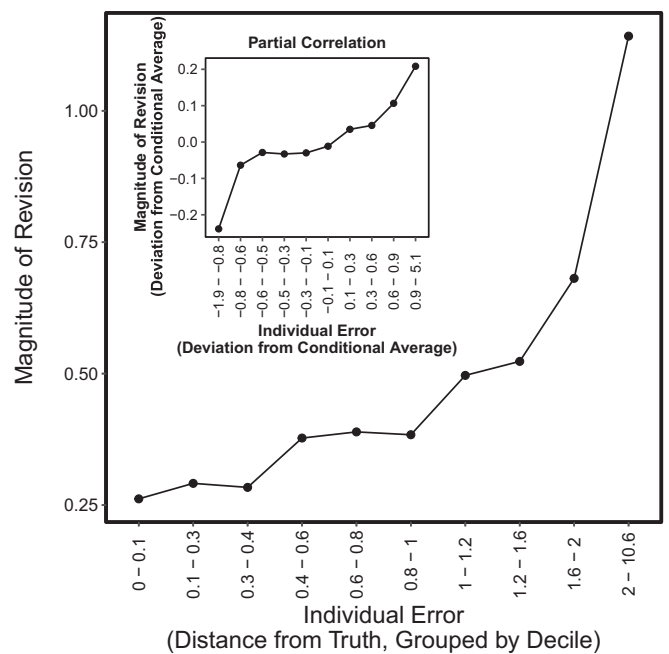


Fig. 2. Correlation between revision magnitude and individual error. Each point in the main graph shows the average size of individuals' revisions from round 1 to 3 for individuals located in each decile of the distribution of individual error (i.e., average distance from zero error), measured for $n = 4,340$ estimates provided by 1,040 individuals assigned to one of 13 decentralized networks or 13 centralized networks. The graph shows a positive "revision coefficient," such that individuals with greater error in their initial estimates made significantly larger revisions. Controlling for correlation between estimates by the same individual (*SI Appendix*), we find a positive correlation between individual error and individual revision magnitude ($n = 4,340$, $\rho = 0.41$, 95% CI [0.39, 0.43], $P < 0.001$). (*Inset*) On the y axis, positive values indicate larger revisions than would be expected based on the distance between an individual's estimate and their neighborhood estimate. On the x axis, positive values indicate greater initial error than would be expected given the distance between an individual's estimate and their neighborhood estimate. After controlling for the distance between each individual's initial estimate and the average estimate of their neighborhood, there is still a significant correlation between individual error and individual revision magnitude ($n = 4,340$, $\rho = 0.25$, 95% CI [0.22, 0.28], $P < 0.001$).

social influence weight in the network, which can pull the group estimate toward a more accurate mean (*SI Appendix*). These analyses suggest a direct positive relationship between the average revision coefficient among the members of a group and the expected improvement in the accuracy of the group mean. Fig. 3*A* shows, for decentralized networks, the correlation between the improvement in the group mean for each question and the group's revision coefficient for that question for each of the 59 group estimation tasks completed in decentralized networks. Because each group completed multiple estimation tasks, these analyses control for correlations across multiple estimates made by the same group (*SI Appendix*).

Consistent with our theoretical expectations, the correlation shown in Fig. 3*A* indicates that, in decentralized networks, groups with higher revision coefficients also exhibited larger improvements in group accuracy ($n = 59$ estimation tasks, $\rho = -0.71$, 95% CI [-0.82, -0.56]). By contrast, Fig. 3*B* shows that centralized networks (as discussed below) exhibited no significant correlation between a group's average revision coefficient and a change in group accuracy ($n = 57$ estimation tasks, $\rho = -0.16$, 95% CI [-0.33, 0.10]).

Fig. 3*A* indicates that, in decentralized networks, the greater the correlation between individual accuracy and self-weight, the more likely it is that the group mean will improve. Additional

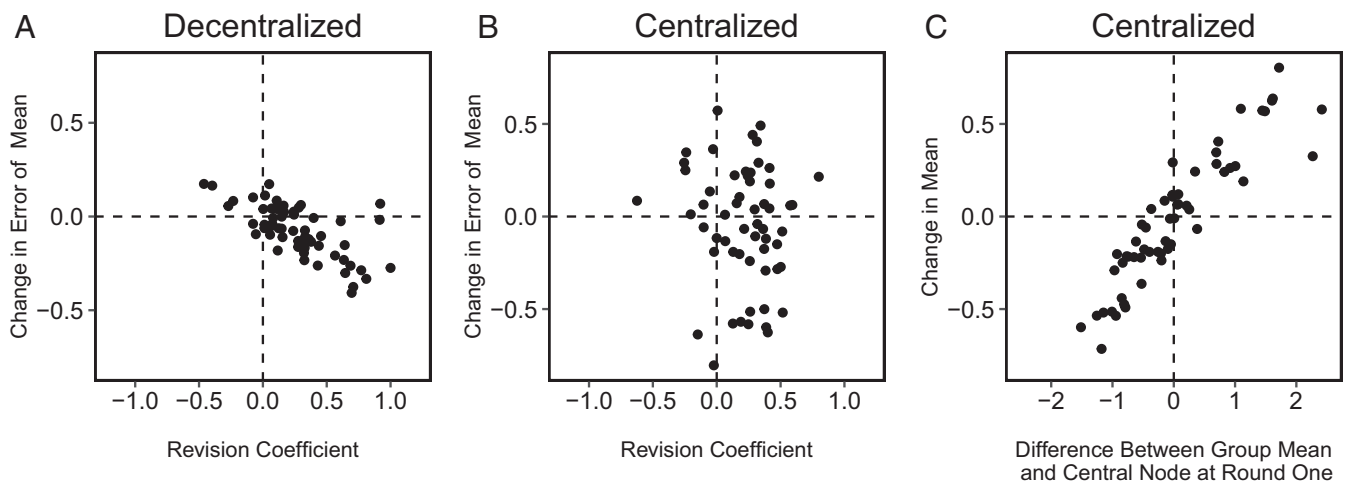


Fig. 3. Correlations with changes in group mean. Shown are all 59 estimation tasks completed over 13 experimental trials. In centralized networks, two estimation tasks are omitted, where the central node did not provide any response. Decentralized networks show all 59 estimation tasks. (A) In decentralized networks, the revision coefficient for each group estimate—i.e., the partial correlation for all members of a network between individuals’ accuracy and their revision magnitudes on a given estimation task—is highly correlated with the change in the error of the group mean ($n = 59$, $\rho = -0.71$, 95% CI $[-0.84, -0.51]$). On estimation tasks in which groups exhibited larger revision coefficients, they showed significantly greater improvements in the accuracy of the group mean. (B) By contrast, in centralized networks, there was no significant correlation between the revision coefficient and the change in group mean ($n = 57$, $\rho = -0.16$, 95% CI $[-0.33, 0.10]$). (C) In centralized networks, the change in the group mean is strongly correlated with the behavior of the central node. The difference between the initial group estimate and the initial estimate of the central node is highly correlated with the change in the group’s estimate ($n = 57$, $\rho = 0.92$, 95% CI $[0.88, 0.95]$). When the central node had an estimate larger than group mean, the group mean typically increased; when the central node was below the group mean, the group mean typically decreased.

simulation analyses, which are provided in *SI Appendix, Fig. S9*, show that in decentralized networks, a positive revision coefficient is sufficient to produce increases in group accuracy, consistent with our empirical findings. Notably, across all experimental trials, the average revision coefficient for all subjects was positive (*SI Appendix*), suggesting that, in very large populations with decentralized networks, social influence is likely to generate consistent improvements in the accuracy of the group mean.

Control Condition. These improvements in both the mean and the median, as well as the accuracy of individuals’ estimates, all contrast with the results from the control condition (i.e., without social influence). Subjects in the control condition were able to revise their answers several times, but were not provided any information about the estimates of other participants. Between rounds 1 and 3, groups in the control condition showed only a small (3%) decrease in average SD (*SI Appendix*), which was significantly smaller than the reduction in diversity in decentralized networks (43%) and centralized networks (42%) ($n = 21$; 13 experimental and 8 control trials, $P < 0.001$ for both comparisons, Wilcoxon rank sum test). The opportunity for revision produced a small (3%) decrease in average individual error even in the absence of social information ($n = 8$ control trials, $P < 0.001$, Wilcoxon signed rank test). However, this improvement was significantly smaller than the 23% improvement by individuals in decentralized networks ($n = 21$; 13 experimental and 8 control trials, $P < 0.001$, Wilcoxon rank sum test). Moreover, in the control condition, these individual improvements produced no significant changes in the accuracy of either the group mean ($P > 0.94$) or the group median ($P > 0.64$) (complementary analyses provided in *SI Appendix*). These results indicate that the improvements in collective judgment observed in decentralized networks are not explained by independent learning effects, but are due to the network dynamics of social influence.

Centralized Networks. To analyze these effects, we divided the group estimates in centralized networks into two categories, based

on the initial estimate of the central nodes. In one category (“center toward truth”), the influence of the central node is expected to increase the accuracy of the group mean. This category includes estimates in which the central node was more accurate than the group mean, and also estimates in which the central node was less accurate, but was on the opposite side of the truth from the group mean. For instance, if the true value is 100 and the group mean is 90, a central node with an estimate of either 105 (more accurate) or 120 (less accurate) will pull the group toward the truth (*SI Appendix, Fig. S8*). The second category (“center away from truth”) includes trials in which the estimate of the central node pulled the group mean away from the truth—for instance, if the estimate of the central node is instead 70. This analytical strategy was used to identify the effects of social influence on both the group mean and the group median, as reported below.

All 13 trials produced responses to at least one question in which the central individual was away from truth relative to the group estimate, whereas only 12 trials produced responses where the central individual was toward truth. Accordingly, our analyses for each category use $n = 13$ trials and $n = 12$ trials, respectively. As shown in Fig. 1 B and C, when the central individual’s estimate was toward truth, the average error of the group mean after social influence (0.32 SD) was 43% lower than the average error of the group mean before social influence (0.56 SD), producing a significant increase in group accuracy ($n = 12$ trials, $P < 0.01$, Wilcoxon signed rank test). Correspondingly, the same analysis for the median showed that the error of the median also decreased significantly by 48% in these group estimations from round 1 (0.70 SD) to round 3 (0.36 SD) ($n = 12$ trials, $P < 0.01$, Wilcoxon signed rank test). Similarly, when the central individual provided an estimate that was away from truth, social influence increased the error of the group mean by 19% and the error of the median by 32% (Fig. 1 B and C), significantly reducing the accuracy of both the mean and the median of estimates ($n = 13$ trials, $P < 0.01$ for both comparisons, Wilcoxon signed rank test).

Fig. 3C shows the effects of the central node on the collective estimate for each of the 57 estimation tasks in which the

central node offered a response. As described above, because each group completed multiple estimation tasks, these analyses control for correlations between multiple estimations made by the same group (*SI Appendix*). The positive slope in Fig. 3C ($n = 57$ estimation tasks, $\rho = 0.92$, 95% CI [0.88, 0.95]) indicates that the group estimates in centralized networks moved toward the initial belief of the central individual—i.e., higher estimates by the central node made the group mean increase, whereas lower estimates made the group mean decrease.

Robustness. To conclude our analyses, we examined the robustness of our theoretical and experimental findings under variations in the network parameters, such as average degree, graph density, and population size. Graph density and average degree had no effect on the results (*SI Appendix, Figs. S13 and S14*). However, we found that the effects of social influence on the wisdom of crowds are significantly strengthened with larger population sizes (*SI Appendix*). Our analyses indicate that recent small-group studies arguing that social influence undermines the wisdom of crowds (even in a decentralized network) (13) were insufficiently statistically powered to identify the improvements in collective accuracy that we found (*SI Appendix, Fig. S15*). Additional simulation analyses, as well as supplementary analyses of the publicly available data from these studies (*SI Appendix*), show that these effects of population size can both explain the negative findings from previous experiments using small groups and demonstrate the generalization of our positive results to larger population sizes.

Discussion

Our study differs in several respects from previous work on the network dynamics of collective intelligence. Unlike research on social coordination (28, 32, 33) and group problem-solving (34–36), our study does not consider situations where social interaction is necessary for groups to achieve a collective outcome. Instead, we identify how the network dynamics of social influence can affect collective estimation tasks in situations where social influence has been predicted to have a negative effect on the quality of group judgments (2, 11–18). Our finding that groups have the ability to generate accurate estimates, even in the presence of social influence, has useful implications for the design of several kinds of collective decision processes. As described in previous studies (13), if social influence did indeed undermine the wisdom of crowds, then democratic institutions and organizational decision procedures could be improved by preventing people from communicating during a voting process (13). Based on these ideas, commercial and nonprofit organizations have implemented automated aggregation tools to collect individuals' independent beliefs in ways that minimize the information exchanged between them (37). Our findings argue against this approach to aggregation. In contrast, we have shown how social learning in networks can amplify the influence of accurate individuals, leading to both individual and collective judgments that are more accurate than those that could typically be obtained by independent aggregation alone. We therefore anticipate that process interventions within political discussion settings (38) and organizational decision contexts (2, 39) may benefit more from approaches that manage communication networks, rather than approaches that attempt to increase independence in the aggregation process.

Materials and Methods

All subjects who participated in this study provided informed consent during the registration process, and all procedures in this study were approved by the Institutional Review Board of the University of Pennsylvania. Upon entering the experimental platform, participants were randomly assigned to one of three conditions—a decentralized random network, a centralized network, or a control condition (*SI Appendix*). Once placed into a condition, players interacted in real time for a period of approximately 15 min. For each question, participants first provided an independent estimate without any social information. In the network conditions, participants observed the average response of the peers immediately connected to them in a social network and were prompted to submit their answers again. Subjects were exposed to two rounds of social influence before they submitted their final answer, providing a total of three responses to each question. In the control condition, participants were given three opportunities to respond, but were not provided any social information. Monetary rewards were based on the accuracy of subjects' final response to each question.

To ensure that our findings are robust to variations in the distribution of estimates, we conducted two sets of experimental trials, using questions that generate distributions with different shapes. In the first set of trials, subjects were given count-based questions (e.g., “how many candies are in this jar?”). Because these are zero-bounded on the left and unbounded on the right, count-based questions generate highly skewed distributions (1, 13), in which the median is able to improve even if the mean remains unchanged (*SI Appendix*). In the second set of trials, we asked participants to provide responses to percentage-based question (e.g., “what percentage of people in this photograph are wearing hats?”). These responses are constrained to fall between 0 and 100, and did not produce any systematic skew in the distribution of estimates (*SI Appendix*).

A single experimental trial consisted of 40 individuals placed into a decentralized network and 40 individuals placed into a centralized network, all of whom were given the same question set. A control group consisted of 40 independent individuals who were all given the same question set as the 80 subjects in the corresponding experimental trial. Because the subjects in a control trial were independent from one another, only one control trial was conducted for each question set.

In trials where we provided count-based estimation tasks, each group completed four tasks. We conducted six independent experimental trials of this kind of task, with four questions each, producing a total of 24 count-based estimations by decentralized networks and 24 count-based estimations by centralized networks. We used a unique question set for each trial, yielding six unique question sets. To create independent control groups for each question set, we ran 6 independent control groups, each with 40 individuals, producing 24 control group estimations.

In trials where we used percentage-based estimation tasks, each group completed five estimation tasks. We conducted 7 independent experimental trials of this kind of task, with 5 questions each, producing a total of 35 percentage-based estimations by decentralized networks and 35 percentage-based estimations by centralized networks. We used two unique question sets, which were randomly assigned across trials. One set was used in three of the trials; the other was used in four of the trials. To create independent control groups for each question set, we ran two independent control groups, each with 40 individuals, producing 10 control group estimations. Because control groups are composed of statistically independent individuals, we only required a single control group for each question set to compare with the experimentally replicated trials. In total, we observed 59 estimations by decentralized networks, 59 estimations by centralized networks, and 34 estimations by control groups.

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