GROUP SIZE, COMMUNICATION, AND COMMON-VALUE PUBLIC GOODS

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ABSTRACT. We experimentally examine the effect of group size on communication in a common-value public goods game. Each player observes a private signal correlated with the uncertain return to contribution and sends a cheap-talk message to the group before making a contribution choice. There is a private incentive to exaggerate the expected return to encourage others to contribute. In theory, this incentive varies non-monotonically with group size due to the increase in potential contributors and the decrease in the likelihood of the message sent being pivotal in others' contribution decisions. Experimental results show that the frequency of exaggeration increases with group size, but communication still increases the frequency of efficient contribution decisions across all group sizes.

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1 INTRODUCTION

Social dilemmas occur frequently in many contexts, including public goods and common-pool resources, where individual incentives often conflict with the collective best interest of a group. These dilemmas vary in scale, from small groups like workplace teams, neighborhood associations, and research collaborations, to large-scale efforts such as international climate-change mitigation.

A key challenge of these dilemmas is that the benefits of cooperation are often uncertain, and information about those benefits may be decentralized. For example, in joint business ventures, each party may possess different private information about the uncertain investment return. Similarly, the effectiveness of pollution abatement and climate-change mitigation strategies is often uncertain and difficult to assess collectively. These are examples of common-value public goods (CVPGs), where the public good is equally valuable to everyone, but the value is uncertain, and individuals may observe different private information about the value. This important type of social dilemma remains understudied.

We consider a public good of uncertain value, where individuals privately observe a noisy signal about the common return to contribution. While these signals are imperfect, they provide useful information about the true value of the public good and can inform individual contribution decisions. When individuals can communicate with each other, information sharing becomes a second social dilemma embedded in the decision environment. Group members may attempt to inform others about what they know (their signals), and this information could potentially improve decision-making. However, because of free-riding incentives, individuals may exaggerate their signals by *always* reporting a high value. Doing so encourages other group members to contribute to the public good which, all else constant, would increase an individual's private gain. As a result, in equilibrium, communication becomes uninformative as group members cannot credibly reveal what they know to others. Nevertheless, if truthful communication were possible, it could enhance efficiency by reducing uncertainty about the expected benefit of contributing to the public good.

A relevant example is co-authorship in research projects. If a coauthor privately doubts the potential quality of the project, they may have an incentive to overstate its prospects to encourage others to invest more time and resources into improving it. This tactic might be more effective in smaller groups, where a single coauthor's opinion carries more weight. However, as the number of coauthors increases, the likelihood that one individual's exaggerated claim influences the group decreases, given the competing signals from other coauthors.

A similar scenario can occur in joint business ventures, where partners may overstate profitability to motivate others to increase their investment, despite uncertainties about the actual returns. A third example is the use of cover crops, which provide environmental benefits such as reducing erosion and nutrient loss (Hoorman, 2009). However, these benefits are uncertain, and beliefs about these benefits may differ between individual farmers (Wilson et al., 2014). This creates an incentive for individuals to exaggerate the expected benefits to encourage their neighbors to plant cover crops.

Understanding the role of group size in the context of common-value public goods is especially important because the potential for socially beneficial information aggregation increases in group size, but the incentive effects of group size are unknown. We use a laboratory experiment to examine how varying group size affects truthful communication and contributions to the CVPG. We examine groups of 3, 7, and 21 individuals. Assuming individuals believe others will contribute if the majority of information indicates a high return, we predict a non-monotonic relationship between group size and the incentive to lie. As group size increases from 3 to 7, the incentive to lie increases, but as size increases from 7 to 21, the incentive to lie decreases. This non-monotonicity arises from two opposing effects: (1) as group size increases, there are more potential contributors in the group who might be swayed by a lie, increasing the incentive to lie, but (2) as group size increases, the probability that a single lie is pivotal (i.e., that a dishonest high message tips the scale of messages to majority high) decreases, reducing the incentive to lie. Thus, we test whether increasing group size has a non-monotonic effect on the frequency of lying and whether the effectiveness of communication varies with group size.

Contrary to the hypothesized non-monotonic effect of group size, our experimental results show a small but significant reduction in truthfulness as group size increases. Despite reduced truthfulness, communication improves the efficiency of contribution choices and the benefits of communication increase with a larger group size. Our overall results show that communication can effectively aggregate information and improve efficiency in larger groups, despite somewhat more frequent misreporting.

2 Related Literature

Several studies have examined the effect of varying group sizes on outcomes across various experimental settings (Weber, 2006; Carpenter, 2007; Charness and Yang, 2014; Duffy and Xie, 2016; Riedl et al., 2016; Hommes et al., 2021; Jensen and Markussen, 2021; Arifovic et al., 2023; Mollerstrom et al., 2024). In the realm of public goods provision, the seminal study by Isaac et al. (1994), which used extra credit instead of cash, finds that larger groups (of up to 100 participants) achieve higher efficiency levels than smaller groups when the marginal per capita return (MPCR) is relatively low (MPCR=0.3). However, they find no significant efficiency gains with a higher MCPR (MPCR=0.75). Similarly, Diederich et al. (2016) observe a positive group size effect, even though subjects anticipate (or expect) efficiency to decline with group size due to free-riding. Weimann et al. (2019), using lower MPCRs (0.02 and 0.04), also report a positive group size effect, but note that larger groups may be more sensitive to small changes in the MPCR. The results of Nosenzo et al. (2015) are somewhat mixed. While their findings align with previous studies in showing a positive group size effect with a low MPCR, they also find evidence of a negative group size effect at a higher MPCR.[1] In our setting, all subjects value the public good equally, but do not know the true benefit of providing the public good (i.e. the MPCR is not known with certainty). Instead, subjects receive noisy signals regarding the state of the world and expected benefits. The expected MPCR with all group sizes in our design is 0.62 (50% chance of 0.04 and 50% chance of 1.2).

Some, but not all, experiments investigating public goods with uncertain returns have found that contributions tend to be lower when uncertainty is present (see e.g. Dickinson, 1998; Gangadharan and Nemes, 2009; Levati et al., 2009; Stoddard, 2017; Blanco et al., 2016, 2017; Aksoy and Krasteva, 2020; Boulu-Reshef et al., 2017; Theroude and Zylbersztejn, 2020). Fewer studies examined uncertainty with decentralized private information about the return to contributing to the public good, i.e. common-value public goods. Cox (2015), for instance, examines a common-value threshold excludable public good (or club good) and finds improper belief conditioning related to the winner's curse in common-value auctions (Thaler, 1988; Kagel, 1995; Kagel and Levin, 2002). Calford and Cason (2024) examine a similar environment with static and dynamic contributions, finding that the dynamic contribution mechanism does not reduce contributions, contrary to the equilibrium prediction. Marini et al. (2020) examine ambiguity and decentralized information in a threshold public good, finding that pre-play communication increases contribution, but unexpectedly low returns can reduce cooperation in later rounds. Butera and List (2017) examine a linear public goods game with Knightian uncertainty and private information about the return to contribution, finding that more uncertainty leads to higher contributions. We examine a static linear common-value public good where group members receive noisy signals about the true value of the public good. We vary group size and whether members can send cheap-talk messages to other group members.

[1]Another relevant study is Carpenter (2007), which explores how monitoring and punishments are affected as group size increases. Carpenter (2007) shows that sanctions are a useful deterrent against free-riding, even as group sizes increase.

While uncertainty and private information can affect individual actions, the methods by which this information can be used and communicated to others can also affect outcomes. Several related papers on leading by example consider a single informed first-mover interacting with one or more uninformed second-movers (e.g. Hermalin, 1998; Vesterlund, 2003; Potters et al., 2005; Andreoni, 2006; Potters et al., 2007). In these studies, first-mover contribution tends to increase second-mover contribution. Related to the current study, Komai and Grossman (2009) find that leading by example becomes less effective as group size increases. Similarly, Feltovich and Grossman (2015) show that pre-play communication (where group members can propose contribution strategies) can improve cooperation in a threshold public goods game, but messages become less effective as group size increases. Using a public goods game with heterogenous types, Robbett (2019) finds that participants tend to reveal their types truthfully, and this honesty translates into higher contributions. Nevertheless, communication also provides an opportunity for strategic dishonesty. Serra-Garcia et al. (2011) and Foerster and van der Weele (2021), for instance, examine first-mover cheap talk and find evidence for strategic lying.[2] Irlenbusch and Ter Meer (2013) find that subjects can behave opportunistically in a public good setting where actual contributions are unknown. We find that subjects are relatively truthful when sending messages about their private signals of the value of the public good. However, the rate of truthful messages declines as groups become larger.

Our design most closely resembles Cox and Stoddard (2021). In a setting similar to ours with a fixed group size of three, they find that messages are exaggerated, but much more truthful than the equilibrium prediction. Truth-telling and trust lead to significantly higher efficiency compared to settings without communication. Most subjects follow a behavioral heuristic of contributing (not contributing) if the majority of the information received, including their signal and the messages from others, indicates the CVPG would yield a high (low) return from contribution. However, they find less truthful messages and smaller benefits from communication when signal accuracy or the distribution of possible returns to contribution are modified to increase the incentive to lie. Thus, participants provide the informational public good of truthful communication, but such provision is sensitive to incentives against truthfulness.[3] As we discuss in Section 4, the incentive to lie also varies with group size. We examine whether varying this incentive affects the frequency of truthful

[2] Dishonesty or misreporting can also become more pronounced in group settings (Kocher et al., 2018; Conrads et al., 2013). Jiang and Villeval (2024) examine a setting where lying increases the likelihood of collective sanctions, finding evidence of more frequent lying in larger groups.

[3] Raeburn et al. (2023) also study the provision of information as a public good in a different context. Participants can choose an ambiguous gamble, the outcome of which provides others with information about its distribution.

messages and whether the benefits of communication found by Cox and Stoddard (2021) are robust to changes in group size.

3 Experimental Design and Procedures

At the beginning of each session, subjects are randomly assigned into groups of size 3, 7, or 21 (thus, each session had 21 participants). These groups remain fixed for the duration of the block, which consists of ten decision rounds. Each session consisted of 3 blocks. In each decision round, subjects are endowed with 25 tokens and must decide whether to contribute *all* 25 tokens to either a group account or to a private account. Partial contributions are not allowed. The group account's MPCR can be High (MPCR=1.2) or Low (MPCR=0.04) with equal probability.[4] Each subject receives a private noisy signal about the group account's actual MPCR. Private signals are iid conditional on the true MPCR, and subjects are informed that their observed signal is accurate with 70% probability.

In treatments with no communication, subjects first observe their private signals and then decide whether to contribute all 25 tokens to the group account or keep them in their private account. In treatments with communication, in addition to receiving their private signal, subjects are also asked to send a message ("High" or "Low") to others in their group before making a contribution decision. Before observing messages from other group members, each subject is also asked to develop a decision-making rule to be executed by the software. This rule specifies how their 25 tokens will be allocated based on the number of High messages received from the other group members. These decisions are not required to be monotonic in the number of High messages received. Subjects are free to ignore or factor in the information provided by their signal and, when applicable, their group members' messages.[5]

In both treatments, after submitting their allocation decisions, subjects observe a results screen that displays the total number of tokens allocated to the group account, their private signal, the true state (High or Low), their share of the group account, and their payoff for that round. In treatments with communication, a subject also observes the message he/she sent,

[4]We set MPCR = 0.04 to ensure that contributions remain inefficient for every group size in the experiment. With our largest group size of $N = 21$, the threshold for individual contribution to be privately efficient is MPCR $\geq 1/N \approx 0.0476$. Choosing MPCR $\leq 1/N$ guarantees that full provision is socially inefficient across treatments. Nevertheless, even at MPCR = 0.04, a subject who persuades one additional contributor can increase their own payoff, creating an incentive to misreport their signal in communication treatments.

[5]The strategy method enables us to elicit full conditional contribution rules, thereby providing more information on how individuals respond to these messages. While this may focus subjects' attention on the mapping between messages and contributions, subjects were not constrained to monotonic responses and could ignore group messages. Importantly, Cox and Stoddard (2021) report that contribution decisions are robust across direct-response and strategy-method designs, although the latter can influence messaging behavior.

Table 1. *Session Summary*

	Group Size		
Communication	Block 1	Block 2	Block 3
No	3	7	21
No	7	21	3
No	21	3	7
Yes	3	7	21
Yes	7	21	3
Yes	21	3	7
Yes	3	21	7
Yes	7	3	21
Yes	21	7	3

and the number of High/Low messages received from other group members. It is important to note subjects never observe the private signals other group members received.

After ten rounds, the block ends, and subjects are regrouped into one of the two remaining group sizes. Once the new block begins, subjects make decisions as described above. After ten rounds, the final block begins. To illustrate, consider the following example. If the first block places subjects into seven groups of 3, then the second block will consist of three groups of 7 or a single group of 21. The final block consists of the remaining group size. Where possible (group sizes 3 and 7), groups are randomly and anonymously determined. Subjects were paid based on two randomly chosen rounds from each block (i.e. paid for six of the 30 rounds). Note that we have twice as many communication sessions as no-communication sessions. We increased the sample size with communication to examine a variety of conditional means based on messages group members sent and received.

he experiment was programmed and conducted using z-Tree (Fischbacher, 2007). A total of nine experimental sessions were run, each with 21 participants (189 total subject). Table 1 provides a summary of sessions. All sessions were conducted at Appalachian State University between Spring 2022 and Spring 2024. Subjects were recruited by email using ORSEE (Greiner, 2015). At the beginning of each experiment, subjects received printed instructions, and these were read aloud by the experimenter. (Sample experimental instructions are available in Online Appendix Section 2.) Subjects took a comprehension quiz following the reading of the instructions. Each session lasted about 75 minutes. Subjects received a show-up fee of \$10. In total, subjects earned an average of \$26.88.

4 Predictions

As shown in Cox and Stoddard (2021), equilibria of the stage game are babbling equilibria in which messages are uninformative about signals and thus are not believed. Therefore, players must make contribution choices based only on their own signals. The expected MPCR given a High signal is $0.7 \times 1.2 + 0.3 \times 0.04 = 0.852 < 1$, so players will not contribute in equilibrium.[6] The standard backward induction argument extends these equilibrium predictions to the finitely-repeated game.

The incentive for a particular player to exaggerate by sending a High message given a Low signal depends on the strategies of other players. In equilibrium, messages are not credible and do not influence others' contribution choices, and therefore each player is indifferent between sending High and Low messages. However, Cox and Stoddard (2021) find that, in groups of 3, typical participants send truthful messages and follow the majority of the three bits of information available (own signal and two messages from others). Assuming others follow such strategies (and extending the majority rule to larger group sizes of 7 and 21), there is a positive incentive to exaggerate. Player i benefits from exaggerating when the other players' signals are split, and thus i's message is pivotal in the contribution choices of the other players. In particular, as a proportion of the endowment, the incentive to exaggerate is:

$$\Pr(\text{H State}|\text{L Signal}) \times \binom{N-1}{(N-1)/2} \times \Pr(\text{L Signal}|\text{H State})^{(N-1)/2} \times \Pr(\text{H Signal}|\text{H State})^{(N-1)/2} \times (N-1) \times \text{MPCR}_H$$
$$+\Pr(\text{L State}|\text{L Signal}) \times \binom{N-1}{(N-1)/2} \times \Pr(\text{L Signal}|\text{L State})^{(N-1)/2} \times \Pr(\text{H Signal}|\text{L State})^{(N-1)/2} \times (N-1) \times \text{MPCR}_L$$

This incentive varies non-monotonically as group size N increases, as shown in Figure 1 for the parameters in the experiment. In particular, for our parameters and a group of 3, the incentive to exaggerate is 32.6% of the endowment. For a group of 7, this incentive increases to 43.1%, but decreases to 23.9% for a group of 21.[7] This pattern is due to two key effects of increasing group size. First, increasing group size increases the number of contributors that could potentially be swayed by an exaggerated message, increasing the possible reward from such a message. Second, increasing group size also decreases the probability that an individual message will be pivotal because the probability that others' signals are exactly

[6] For example, a natural equilibrium involves every player sending a High message regardless of the signals received. Beliefs about the state are updated according to Bayes' rule conditioned only on one's own signal, and no contribution is made. Similar equilibria exist where messages are uninformative about signals, chosen randomly and independently of signals.

[7] We find a similar non-monotonic incentive pattern if we instead assume that each others player's probability of contribution is a logistic function of the number of high messages and simulate payoffs for exaggerating versus truthfulness, as shown in Online Appendix Subsection 1.7, Figure A.10.

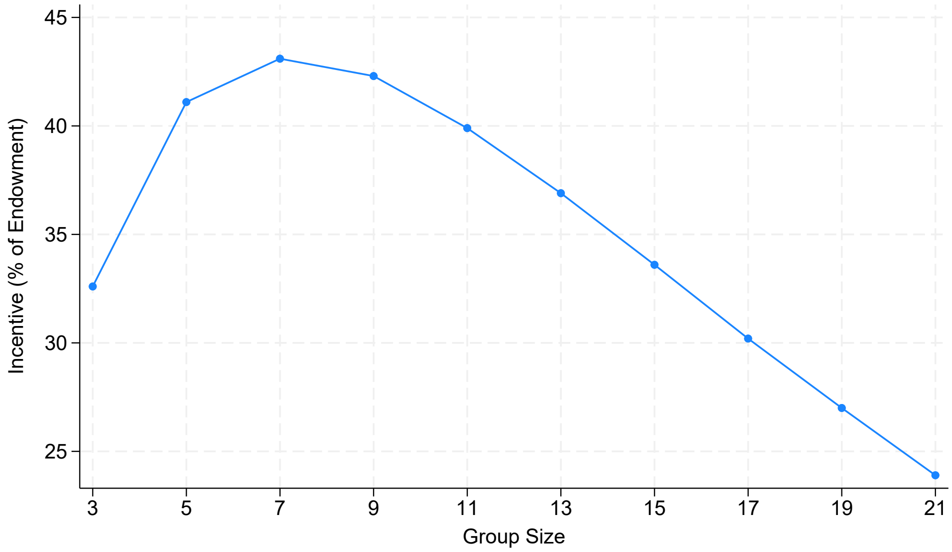

Figure 1. *Incentive to exaggerate (% of endowment) by group size.*

split decreases with group size. These two opposing effects lead to a non-monotonic incentive to exaggerate as a function of group size. This pattern of varying incentives as group size increases from 3 to 7 to 21 leads to our main hypothesis.

Hypothesis 1. Conditional on observing a Low signal, the frequency of truthful messages will be lowest for group size 7 and highest for group size 21.

We also examine whether varying the incentive to exaggerate, by varying group size, affects contribution choices and efficiency. That is, we test the robustness of the benefits of communication found in Cox and Stoddard (2021) to increasing group size.

5 Results

We first examine how truthfulness is influenced in our experimental setting. Figure 2 displays the frequency with which a subject sends a truthful message, conditional on having a Low or High signal, broken down by group size. As expected, truthfulness is consistently high when subjects receive a High signal, regardless of group size. With a Low signal, truthfulness is lower and appears to decrease somewhat with group size. The decrease in truthfulness from group size 3 to group size 7 is consistent with our main hypothesis, but we do not see the hypothesized increase in truthfulness for group size 21.[8]

[8]Online Appendix Subsection 1.1 examines the rates of truthfulness with a Low signal at the individual participant level. For every group size, the majority of participants are always truthful.

Figure 3 shows the frequency of truthful messages for High and Low signals, across all group sizes, over the 10 periods in a block. In early periods, truthfulness rates for Low signals are nearly identical across group sizes. However, truthfulness for group sizes 7 and 21 decline below the rate for group size 3 in later periods.

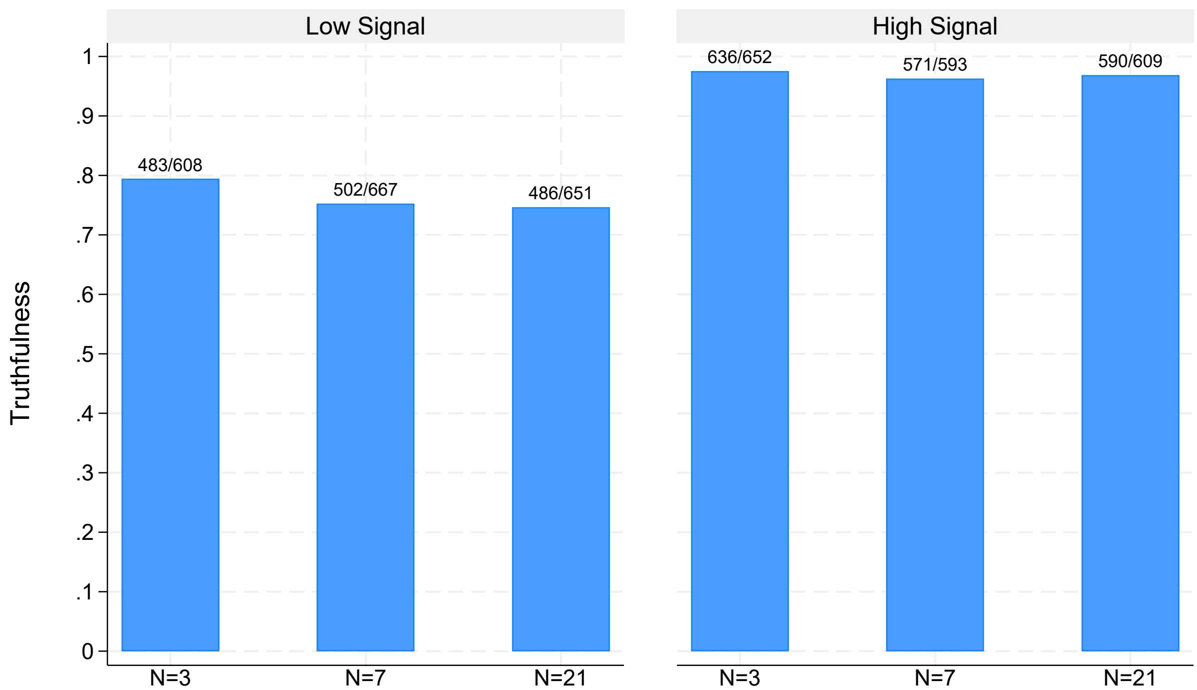

Figure 2. *Truthfulness by signal and group size.*

Table 2 shows linear probability model regression results for truthfulness conditional on a Low signal. We use multilevel models with random effects at the individual and session levels.[9] The most parsimonious models in Columns 1 and 2 show a small but statistically significant decrease in truthfulness for group sizes 7 and 21 compared to group size 3, as well as a significant downward trend in truthfulness in Model 2. In Model 3, we include interactions of Period with group size to capture the divergence of truthfulness rates apparent in Figure 3. In this model, the main effects of group size and Period are no longer significant, but the interactions of Period with group size 7 and group size 21 are significant and negative. This result indicates that truthfulness has a stronger downward trend across periods in larger group sizes compared to group size 3. In Model 4, we include indicators for Block 2 and Block 3 to control for potential order effects. We do find a positive and significant estimate for the

[9]Online Appendix Subsection 1.6 uses a Monte-Carlo simulation approach to estimate the power of t-tests from Model 1 for various effect sizes. We find power of 80% or better for effect sizes of plus or minus 5 percentage points, using two-tailed tests and a 5% significance level.

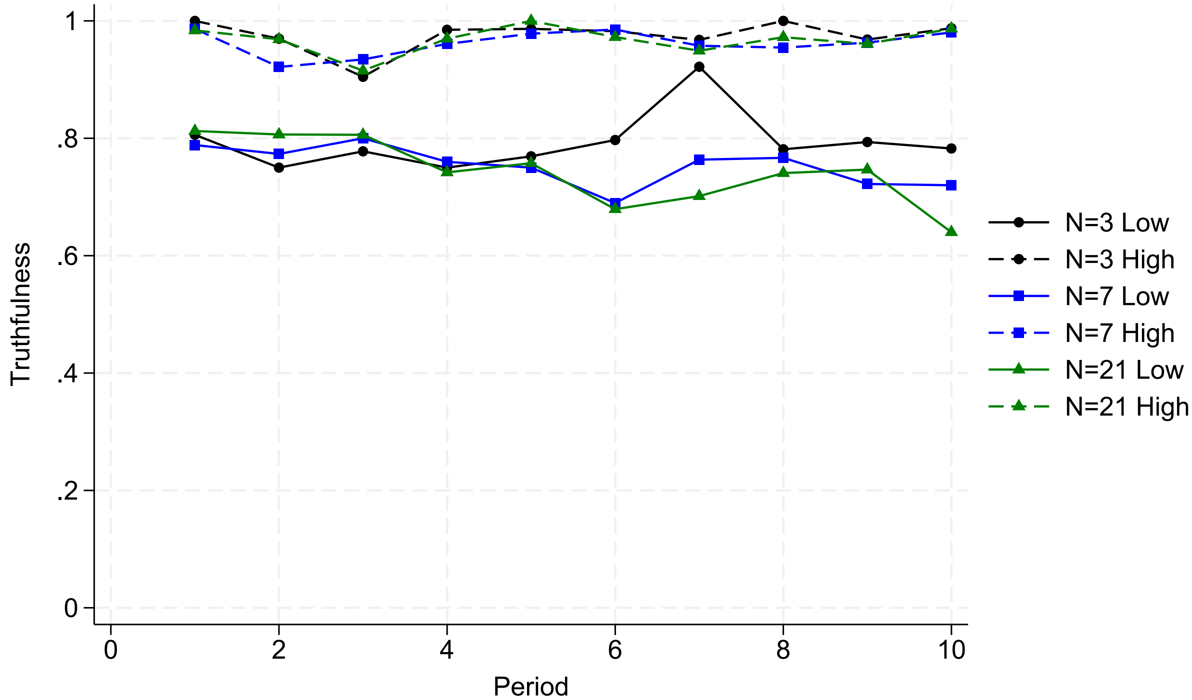

Figure 3. *Truthfulness by period.*

Block 2 coefficient. However, the signs, magnitudes, and significance of the other parameter estimates remain similar to Model 3.[10]

We now turn our attention to contribution rates. Figure 4 shows the contribution rates by signal for each group size with no communication. For all group sizes, a contribution is significantly more frequent conditional on a High signal compared to a Low signal (p-values < 0.001 for each group size).[11] Comparing across group sizes, we find no significant differences with a high signal. With a low signal, average contribution is 5.1 percentage points lower for $N = 7$ compared to $N = 3$, but the difference is only marginally significant (p-value=0.086).

Figure 5 shows contribution rates with communication for each group size, signal, and number of high messages received.[12] Each panel for group size 3, 7, and 21 is broken down by an individual having a Low (left) or High (right) private signal. For instance, if a subject is in a group of 3 and receives a Low signal, but receives two High messages, then this person would contribute approximately 78% of the time. Conversely, if a subject is in a group

[10]Online Appendix Subsection 1.4 further examines the main results for Block-1 data only. The results remain largely similar, though statistical significance is weaker, likely due to the smaller sample size.

[11]Unless otherwise specified, we compare proportions using linear probability models, including multilevel random effects at the session and individual participant levels (Moffatt, 2016).

[12]Online Appendix Subsection 1.5 shows the empirical conditional average MPCR by group size, signal, and high messages received. Online Appendix Subsection 1.2 shows individual-level analysis of contribution conditional on receiving high messages.

Table 2. *Linear probability model regressions for truthfulness conditional on a Low signal. Multilevel models with random effects at the individual participant and session levels.*

	(1)	(2)	(3)	(4)
N=7	-0.0332*	-0.0321*	0.0341	0.0363
	(0.0176)	(0.0175)	(0.0379)	(0.0378)
N=21	-0.0574***	-0.0577***	0.0137	0.0163
	(0.0177)	(0.0176)	(0.0378)	(0.0377)
Period		-0.00619**	0.00253	0.00310
		(0.00251)	(0.00446)	(0.00446)
N=7 × Period			-0.0122**	-0.0127**
			(0.00614)	(0.00612)
N=21 × Period			-0.0133**	-0.0137**
			(0.00624)	(0.00623)
Block=2				0.0551***
				(0.0172)
Block=3				0.0276
				(0.0175)
Constant	0.798***	0.832***	0.785***	0.754***
	(0.0306)	(0.0335)	(0.0391)	(0.0405)
Observations	1926	1926	1926	1926
Participants	126	126	126	126
Sessions	6	6	6	6

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

of 21, receives a high signal, but does not receive any high messages, this person would only contribute approximately 10% of the time. Contrary to the equilibrium predictions, contribution is strongly influenced by messages. For each group size and signal, the frequency of contribution differs significantly by the number of high messages received (joint F-tests, p-values<0.001 in each case).[13] Comparing across group sizes with a high signal and at least 50% high messages received, average contribution is 2.6 percentage points lower for $N = 21$ than for $N = 3$ (p-value=0.014). With a high signal and less than 50% high messages received,

[13]Online Appendix Subsection 1.3 examines contribution rates with communication separately for individuals who send truthful or untruthful messages. We find that individuals who sent untruthful High messages still generally respond to observed High messages by contributing more frequently. Interestingly, in the rare cases of untruthful Low messages, the sender of the untruthful message does not respond to observed High messages with more frequent contributions.

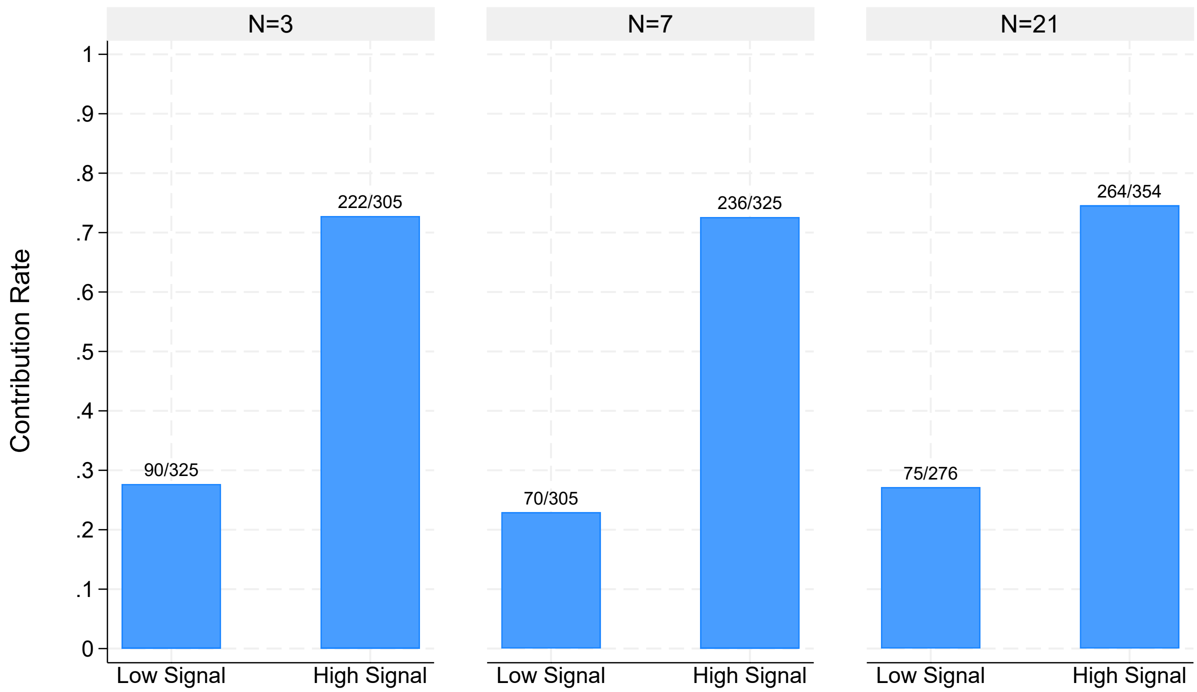

Figure 4. *Contribution rates without communication by group size and signal.*

average contribution is 5.4 percentage points lower for $N = 7$ than for $N = 3$ (p-value<0.001). With a low signal and at least 50% high messages received, average contribution is 13.8 percentage points higher for $N = 7$ and 12.3 percentage points higher for $N = 21$ compared to $N = 3$ (p-values<0.001). With a low signal and less than 50% high messages received, average contribution is 4.9 percentage points lower for $N = 21$ than for $N = 3$ (p-value<0.001).

Figure 6 shows contribution rates by period for each treatment, separately for information indicating a High or Low return. For group sizes of 3 or 7, a downward trend in contribution is apparent with a High Signal and No Communication, but no such trend appears with Communication. For group size 21, there are moderate downward trends both with and without Communication.[14]

Figure 7 shows the contribution rates with and without communication for each group size, signal type, and true state (return to contribution). When the signal correctly matches the true state, contribution rates are similar with and without communication.[15] However, when the signal is incorrect, communication leads to more efficient contribution decisions:

[14]Linear regressions of contribution against Period with random effects at the individual and session levels show statistically significant trends for group size 21, and for group sizes 3 and 7 with No Communication and High Signal.

[15]A minor difference appears for group size 7 in the Low state with a Low signal, but this difference is not statistically significant (p-value=0.300)

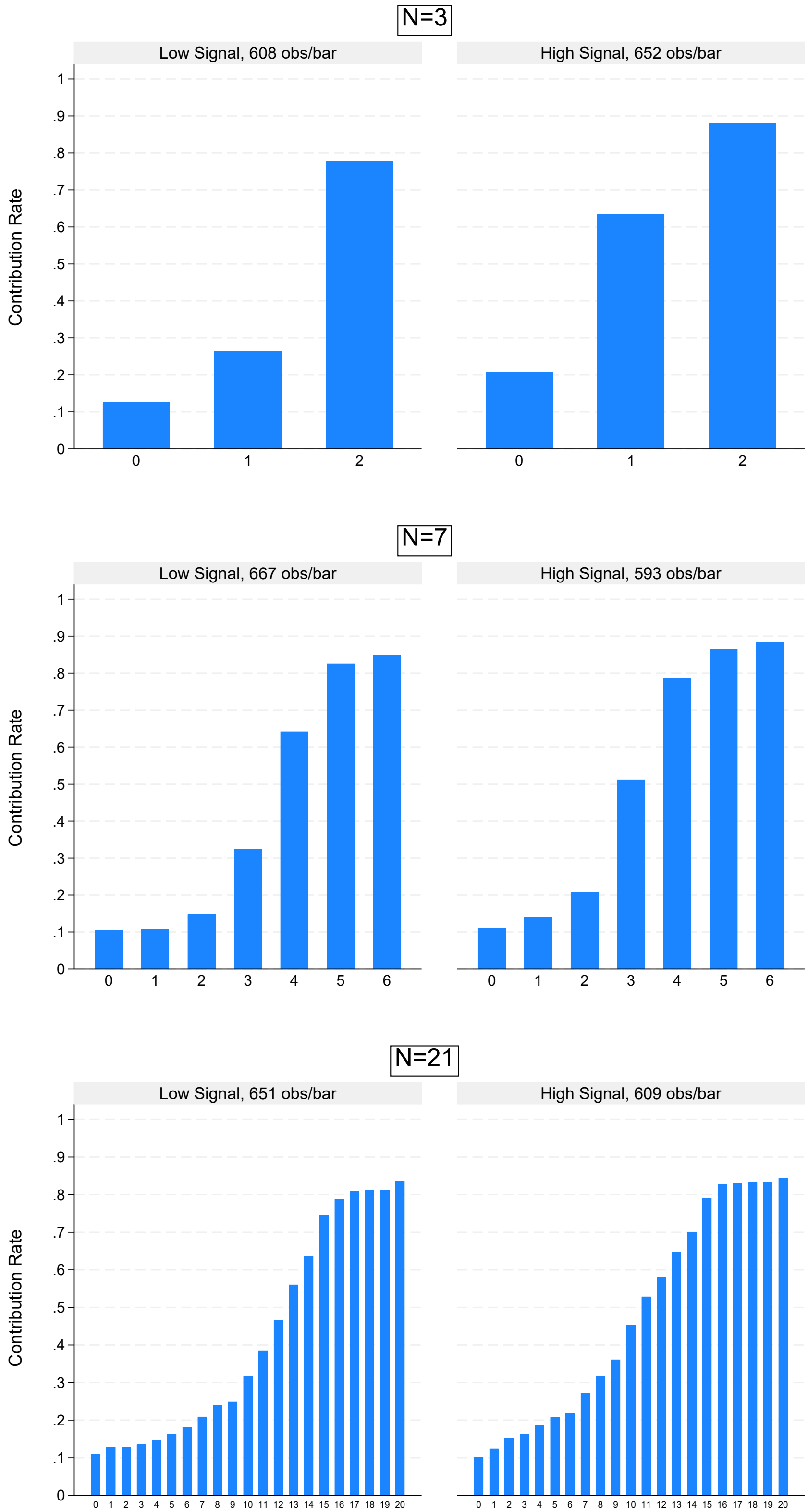

Figure 5. *Contribution rates with communication by group size, signal, and high messages received.*

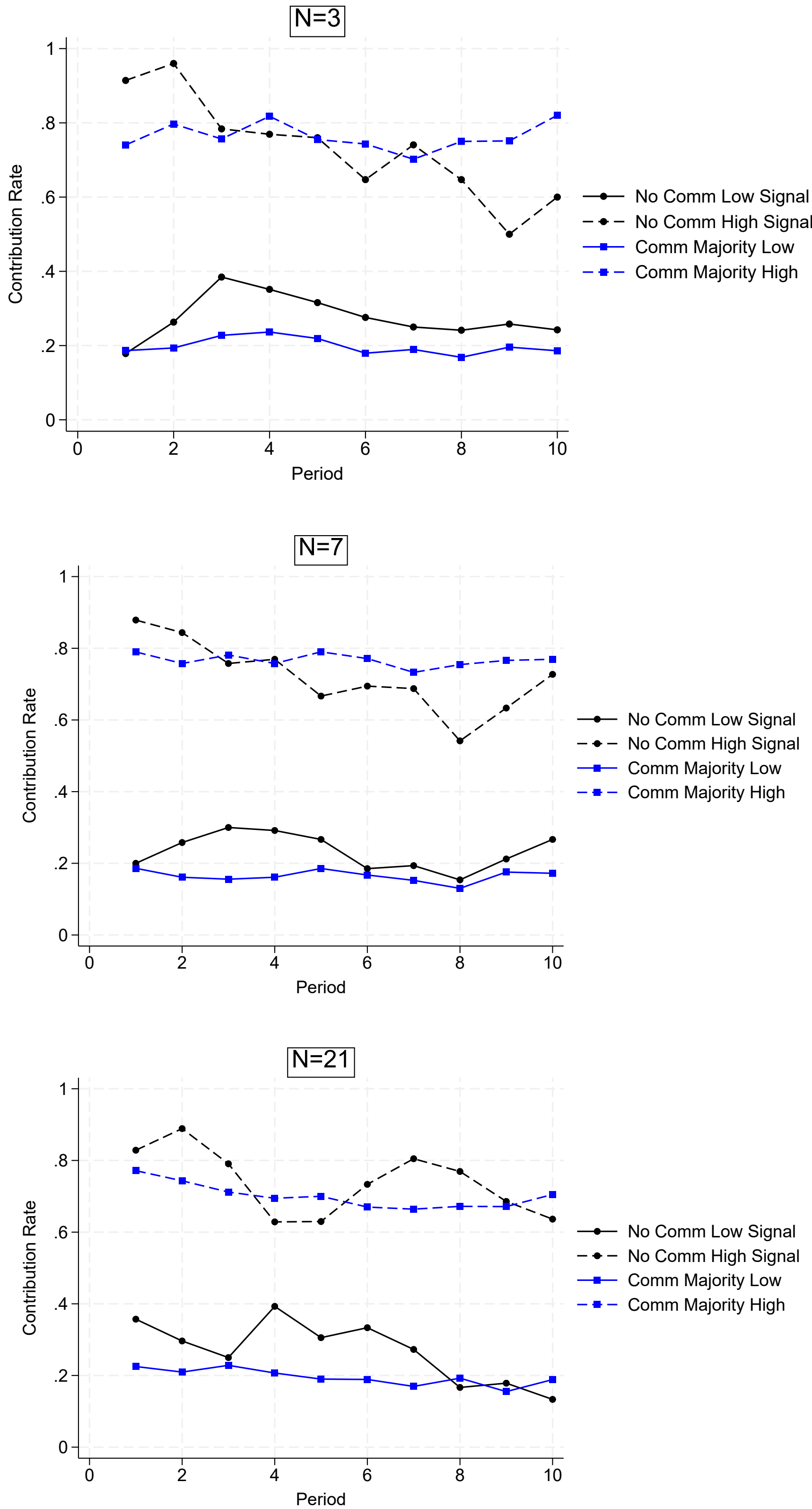

Figure 6. *Contribution rates by period.*

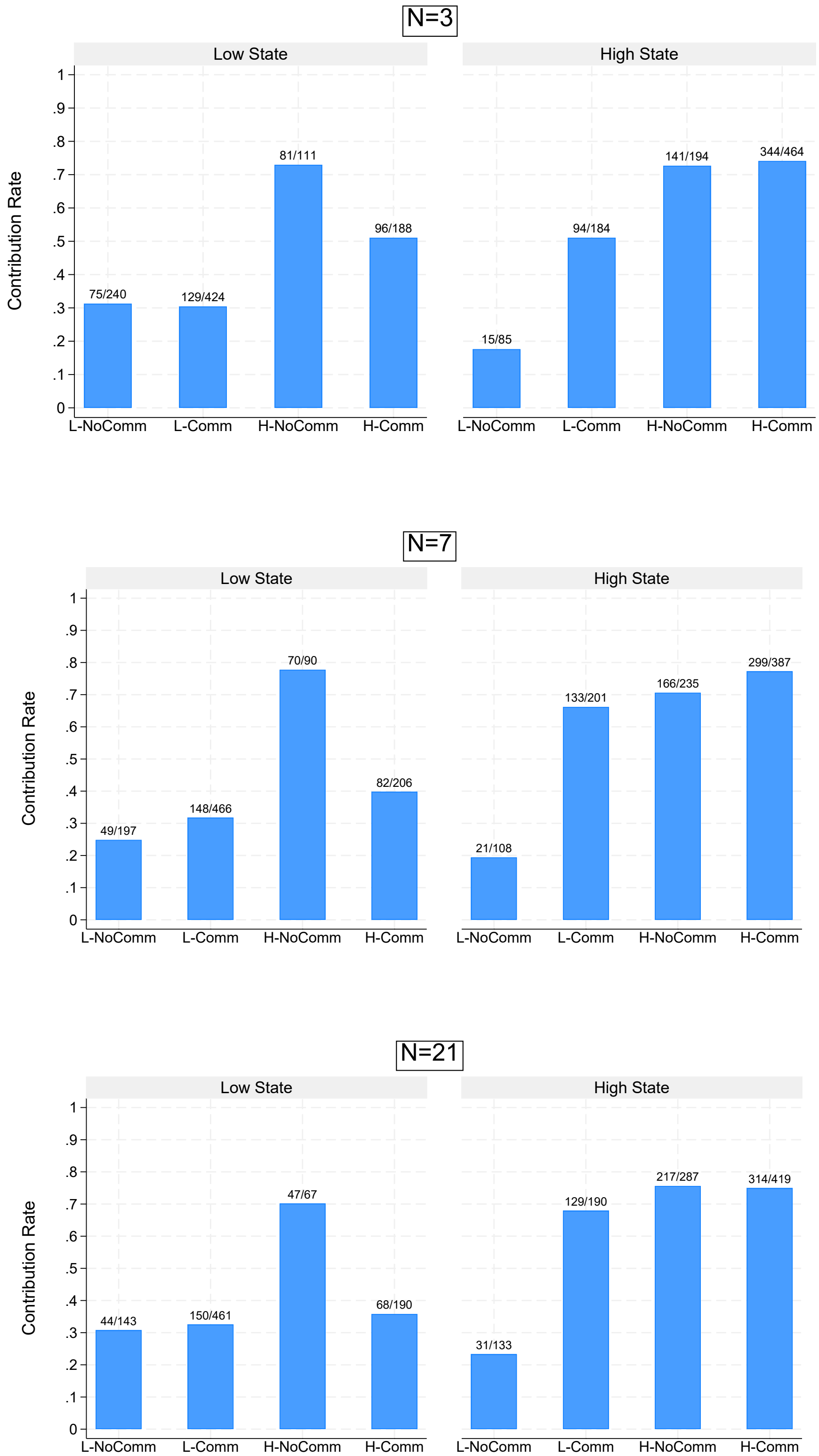

Figure 7. *Contribution rates with and without communication by group size, signal, and state.*

participants contribute more in the High state and less in the Low state with communication than without. For each group size in both the High and Low states, the effect of communication on efficient contribution decisions is statistically significant (all p-values≤0.002). Moreover, we find that this effect is stronger in larger group sizes. In the Low state with a High signal, relative to $N = 3$, communication has a stronger effect in decreasing inefficient contribution for $N = 7$ (p-value=0.031) and for $N = 21$ (p-value=0.074). In the High State with a Low signal, relative to $N = 3$, communication has a stronger effect in increasing efficient contribution for $N = 7$ (p-value=0.032) and for $N = 21$ (p-value=0.043).

6 Conclusion

This paper provides evidence on how varying group size affects communication about the benefits of cooperation. Unlike traditional public good settings, common-value public goods are characterized by uncertainty and decentralized information about the return to contribution to the public good, creating opportunities for socially beneficial information aggregation. We find a small but significant reduction in truthful communication as group size increases. This result is contrary to the hypothesized non-linear effect of group size, which suggests that the incentive to lie initially increases as the number of potential contributors to sway grows, before decreasing due to the declining probability of an exaggerated message being pivotal in others' contribution choices. One possible interpretation of this finding is that the probability of being pivotal may not be as salient to laboratory participants as the potential to sway more contributors.

Despite the somewhat more frequent misreporting in larger groups, we find that contribution choices still respond strongly to messages across all group sizes. Additionally, communication improves the efficiency of contribution choices, with larger groups seeing greater benefits. Thus, our results demonstrate that participants can effectively aggregate information when allowed to communicate, which promotes more efficient contributions in this setting. Moreover, these benefits are robust to increases in group size. The greater benefits in larger group sizes suggest that the positive effect of having more information to aggregate outweighs the small increase in misreporting.

These findings are relevant to groups or organizations where individuals collaborate to achieve a common goal. Our results suggest that individuals consider what they know (their imperfect signal) and act accordingly (i.e., people who observe Low signals contribute less often than those who observe a High signal). Over time and depending on context, team sizes may grow or shrink and team members must adjust their behavior. While teams may face some challenges as they grow, such as misreporting or lying, the collective knowledge of the team members can improve efficiency if it can be aggregated and communicated to others.

Several interesting directions remain for future research. Common-value public goods and information aggregation in such environments remain understudied in the literature, and behavioral responses to various design features and parameter variations are not yet well understood. For example, future research might examine a setting with both private and common-value components, where private values create stronger incentives for misreporting. Another interesting direction might be to examine free-form communication, which might make lying more aversive and allow for communication of intentions of persuasion.

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