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Let's Talk It Over: Communication and Coordination in Teams

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Department of Economics
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Let's Talk It Over: Communication and Coordination in Teams*

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Abstract

Collaboration in teams in which each member's output is critical to the overall success present organizations with difficult coordination problems. We develop a model and run simulations to analyze how costly communication affects team coordination and output efficiency. We show that absent any organizational routines to structure team communication the least efficient outcome is the most frequent organizational output. We then derive formal conditions and simulate efficiency gains for several communication routines that improve team coordination and organizational efficiency. Our model and simulation results match a broad range of findings from the experimental and organizational literature, help explain why collaborations involving several organizational units often fail, and suggest new tests for promising communication routines.

Keywords: Coordination, Communication, Teams, Routines, Authority

JEL Classification: D23, D02, L22, L23, C73

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INTRODUCTION

When tasks are specialized and interdependent, coordination becomes important for organizations and the ability to facilitate coordination is often put forward as a reason for their existence (e.g., Simon, 1991; Grant, 1996; Kogut and Zander, 1996). Understanding why groups may or may not be able to coordinate their actions, and how coordination mechanisms should be designed, is thus key to explaining and improving organizational efficiency.¹

Coordination problems may have their greatest impact in organizational settings where the lowest quality of individual inputs disproportionably affects the output quality for the whole team or organization. This feature is a hallmark of cross-functional teams in which each function is essential for the team's overall success. Examples of such teams include product development in which several departments, or firms, are involved (e.g., Ancona and Caldwell, 1992; Pinto, Pinto and Prescott, 1993; Keller, 2001), surgery teams (Lingard *et al.*, 2004), cancer care teams (Fennell *et al.*, 2010), and research teams (Wildman *et al.*, 2012). It is also reminiscent of services such as security and safety, data collection and other general quality assurance activities. Camerer (2003) mentions the joint production of documents in banks, law and accounting firms, as well as airline departures.

One obvious way to coordinate teams is via communication among team members; that is, by transferring information about what each member intends to do. However, when agents act strategically, voluntary communication does not straightforwardly translate into efficient coordination (e.g., Cooper *et al.*, 1992; Weber *et al.*, 2001; Andersson and Holm, 2013; Kriss, Blume and Weber, 2016). Members of cross-functional teams are also often assigned from different organizational units, which may result in limited work experience with one another. And as a project passes through different stages and requires the input from different units, team membership may blur, shortening work relationships and creating uncertainty with

¹ See, for example, Lawrence and Lorsch (1967), Sinha and Van de Ven (2005), Grandori and Soda (2006) and Sherman and Keller (2011) for evidence of the difficulties in choosing efficient coordination mechanisms.

whom to communicate. Finally, the rise of virtual or global teams with declining levels of co-location of team members adds another layer that increases the need but also the costs for communication and coordination (e.g., Hertel, Geister and Konradt, 2005; Mesmer-Magnus *et al.*, 2011; Daim *et al.*, 2012; Miloslavic, Wildman and Thayer, 2015). A team leader may bring relief, but as cross-functional teams often involve several organizational units, team members may have “double loyalties” as they answer to other managers besides the team leader. Because the composition of such teams may also be in a constant state of flux, leaders may be left with little time to build up the necessary authority or influence (Hackman and Wageman, 2005; Daim *et al.*, 2012).

A large empirical literature documents that team processes in general (e.g., Cohen and Bailey, 1997; Lepine *et al.*, 2008; Mathieu *et al.*, 2008), and internal team communication and information sharing in particular (e.g., Mesmer-Magnus and DeChurch, 2009; Buljac-Samardzic *et al.*, 2010; Sivasubramaniam, Liebowitz and Lackman, 2012) are strongly related to team performance. There are however, to the best of our knowledge, no established best practices for how teams should use communication to solve difficult coordination problems. On the contrary, the findings in the meta-analysis of Mesmer-Magnus and DeChurch (2009) indicate that teams fail to share information in situations in which it is most needed, for example when there are high levels of task interdependence.² The absence of best practices is perhaps not surprising given that researchers and practitioners are confronted with a plethora of organizational parameters on task characteristics, team characteristics, and potential routines to facilitate and structure communication.

In this article we develop a parsimonious model to explore the mechanisms behind coordination problems in teams of common interest with costs to communication. Our goal is to examine when and to which extent communication can help alleviate coordination problems in situations in which communication is most crucial, that is when a team’s output dis-

² Similarly, Fehr (2017) describes results from a lab experiment in which subjects can choose to implement a costly communication technology. Despite communication being necessary to prevent coordination failure in the experiment, only about half the participants are willing to pay the small fee. Participants hence seem to overestimate their ability to coordinate, and underestimate the value of communication.

proportionally depends on the lowest quality input of a single member. Our modeling and simulation choices are inspired by Hollenbeck, Beersma and Schouten (2012) who argue that team performance can be classified into three underlying constructs: *skill differentiation*, the degree to which members have specialized functional capacities that make it more difficult to substitute members; *authority differentiation*, the degree to which decision-making responsibility is vested in individual members or subgroups of the team; and *temporal stability*, the degree to which team members have a history of working together. Skill differentiation motivates the use of the weakest-link game at the core of our model (further described below) as this game reflects the notion that each agent is not easily replaceable in the team’s output function. Authority differentiation motivates our analysis of communication routines that vary the degree to which decision-making power lies within the team: voluntary communication, several initial rounds of mandatory communication, or a team leader with varying degree of authority. Finally, temporal stability motivates our analysis of both simulated short-run outcomes and analytical long-run equilibria.

We use a weakest-link game as the core of the model because in this game the payoff for all participants depends on the lowest level of costly effort chosen by any one participant. In this game, all agents profit from everyone else choosing a high level of effort; hence, if all agents believe that everyone else will provide high effort, the optimal choice is to also contribute high effort, leading to a productive equilibrium. However, choosing high effort is risky because effort is costly and payoff is low if a single player contributes at a lower effort level. As a result, low-effort beliefs breed low-effort actions and a low productivity outcome for the group (Knez and Camerer, 1994).

We embed this game in a repeated framework with recurring interactions between players because this allows us to analyze the dynamics of organizational learning and the speed of convergence toward a steady state under various communication routines. Following the literature on coordination in organizations (e.g., March and Simon, 1958; Cyert and March, 1963; Heath and Staudenmeyer, 2000; Aggarwal, Siggelkow and Singh, 2011), we only require

our agents to be boundedly rational: They have limited foresight and information processing capabilities, and may occasionally experiment or make mistakes. As cross-functional teams often exist only for a brief duration, we run simulations to establish the determinants of efficiency gains when agents have only a few rounds of interaction. We also solve our model analytically to learn why short-term outcomes occur and to pin down the determinants for efficiency gains or losses in teams with stable membership.³

We have three major findings. First, costly *voluntary* communication is unlikely to solve coordination problems, unless teams are very small, incentives to coordinate on efficient actions are extremely strong, or the costs of communication are negligible. The reason is that communication costs, even very small ones, imply that agents have to consider whether their message will change their colleagues' course of action. There is thus a trade-off between lowering the strategic uncertainty for the team and an agent's private costs of communication.

Second, simulations that analyze the transition to the long-run outcome paint a similarly gloomy picture: The low-efficiency states that emerge in the long run have considerable explanatory power also in the short term. This dampens hopes that team coordination may be sustainable at least for a short while before starting to unravel. Encouraging agents to occasionally experiment — that is, allowing them to communicate a higher message or choose a higher action to disrupt a low equilibrium — helps briefly, but only when experiments occur in the messaging (rather than action) phase. Unsurprisingly, coordination unravels more quickly in larger groups, but, remarkably, even teams as small as four subjects are

³ Lab experiments have so far tested only the short-run with typically 8-12 rounds. Formal game-theoretical models of communication have used a variety of games and assumptions about communication costs, information and rationality. Cheap talk models examine the effects of pre-play *costless* communication on outcomes in a variety of games (e.g., Crawford and Sobel, 1982; Farrell and Rabin, 1996). Closest to our model, Ellingsen and Östling (2010) model cheap talk by agents using level-k models of strategic thinking. They find that as long as truth-telling is lexicographically preferred to lying, costless communication facilitates coordination in games with common interest, positive spillovers and strategic complementarities like the weakest-link game. Models of *costly* communication however mostly analyze sender-receiver games with perfectly rational agents and examine how outcomes vary with private information and conflicts of interest between sender and receiver (e.g., Austen-Smith, 1994; Dewatripont and Tirole, 2005; Gossner, Hernandez and Neyman, 2006; Calvo-Armengol, De Marti and Prat, 2009; Wilson, 2014). In a team setting though, members commonly share a basic interest in achieving a joint goal (e.g., Hertel, Geister and Konradt, 2005) and hence conflicts of interest is an unlikely explanation for the coordination difficulties observed in practice and experiments.

typically unable to coordinate on efficient outcomes.

Third, we analyze a number of communication routines. First, mandating communication in *each* round or *fully* compensating agents for communication costs removes the adverse incentives and makes the team coordinate efficiently. Forcing agents to communicate for only several initial rounds improves outcomes, however only marginally. A team leader handling communication may improve efficiency, but not unambiguously so: She must expect agents to choose the communicated action and must have enough authority for efficient coordination to occur. These results matter for the efficiency of cross-functional teams in which team leaders lack the authority to command workers from different units or lack the time to build up authority when membership is fluid.

Throughout the article we compare our model’s predictions to findings from the organizational design and the experimental literature on team coordination. For example, our model proposes a microfoundation for the frequent coordination failures documented in new and inter-organizational collaborations where communication routines are often missing (e.g., Hoopes and Postrel, 1999; Heath and Staudenmeyer, 2000; Zollo, Reuer and Singh, 2002). Our model’s predictions also match key findings from the experimental literature on team coordination and communication: For example, we provide an explanation to the striking differences documented between experiments with costly and costless communication, and why making communication mandatory or fully compensating the costs of communication is much more effective than providing large, partial subsidies (Blume and Ortmann, 2007; Kriss, Blume and Weber, 2016). Our results also shed light on why letting a team leader handle communication may improve outcomes over a no-communication situation but should not be expected to fully solve the coordination problem, and why “lead by example” and letting a team leader communicate voluntarily have similar results (Cartwright, Gillet and Van Vugt, 2013; Sahin, Eckel and Komai, 2015; Dong, Montero and Possajennikov, 2017).

Our model rationalizes and provides support for a number of communication routines: First, mandating communication in every round or fully compensating agents for communi-

cation costs solves the coordination problem. Compulsory checklists or other communication protocols are practical implementations thereof.⁴ Second, bolstering the authority of temporary leaders and avoiding double loyalties by team members helps team communication and coordination.⁵ In contrast, keeping temporary teams small or providing large subsidies to communication is unlikely to achieve the same benefits. Moreover, once a team is stuck in a low-productive equilibrium, it is unlikely to escape this situation by itself but may need external intervention. Our model suggests that the promise from mandating such techniques for only a few rounds to reach a productive equilibrium before reverting to voluntary communication is limited. Yet, this may be driven by our assumption of bounded rationality that includes occasional mistakes and limited recall; hence, testing such a routine in the lab or the field seems like an important undertaking.

We next describe the model and its analytical solution. This is followed by a description of the simulation and its results under a few rounds of play and when organizational routines are used to structure agents' communication. The final section summarizes and provides a brief outlook for promising communication routines in coordination settings with costly communication.

A MODEL OF COMMUNICATION AND COORDINATION IN TEAMS

In this section we propose a simple game-theoretic model which embeds a weakest-link game into a repeated framework that allows for organizational learning across periods by boundedly rational agents. We choose the weakest-link game (as opposed to other order

⁴ For example, surgery teams use checklists for communication before and during operations (Lingard *et al.*, 2004; Wahr *et al.*, 2013), and the airline industry makes use of crew resource management protocols (Salas *et al.*, 2015). Pentland (2012) describes manipulations in the same spirit as our mandatory communication routines, for example scheduling lunch breaks so that teams have to eat at the same time.

⁵ Team leader authority can be improved for example by choosing leaders with more expertise (Wageman and Fisher, 2014), with more supervisory experience (Bonet and Salvador, 2017), or by having members choose their own leader (Brandts, Cooper and Weber, 2014). Graebner (2004) finds that leaders from acquired businesses can help unlock synergies via communication efforts with their departments during the acquisition process. In strictly hierarchical teams (e.g., in surgery, assembly lines, or the military), building strong norms that enforce this hierarchy is another suggestion (Wageman and Fisher, 2014).

statistic coordination games) because it both embodies a very difficult team coordination problem and it is widely used in lab experiments. This in turn facilitates the comparison of the model's outcomes with existing results from the laboratory setting.

The Weakest-Link Game

Suppose a finite set of N agents $I = \{1, 2, \dots, N\}$ and of K actions $A = \{1, 2, \dots, K\}$.⁶ The agents play an infinitely repeated game with the stage game consisting of two simultaneous-move phases: the communication phase and the action phase. The rules of the game are fixed, so we describe an arbitrary round.

First, in the communication phase, each agent either sends a message $m \in A$ or abstains from communicating (denoted $m = \emptyset$). Let $M \equiv A \cup \{\emptyset\}$ denote the set of feasible messaging choices, and the vector of sent messages be denoted in bold-face as $\mathbf{m} \in M^N$. Second, after observing \mathbf{m} , each agent chooses in the action phase an action $a \in A$ (bold-faced $\mathbf{a} \in A^N$ denotes the vector of carried-out actions). Finally, all agents learn the lowest-ranked played action, the *minimum action* denoted as $\underline{a} \equiv \min_{i \in N} a_i \in A$, but do not observe individual actions and the payoff of the stage game is realized.⁷

The payoff in the weakest-link game increases in the minimum action and decreases in the agent's own action. While communicating (sending a message) is costly, $c(m) = \gamma > 0$, it is costless to abstain from communicating, that is $c(\emptyset) = 0$, and to receive messages. The function $u: A \times A \times M \rightarrow \mathbb{R}$ determines the agent's payoff (or utility) when the minimum action played is \underline{a} , she plays a_i , and she sends message m : $u(\underline{a}, a_i, m) = \lambda \underline{a} - a_i - c(m)$. The parameter $\lambda > 1$ quantifies the strength of the incentives to choose a higher-ranked (but also more costly) action: A greater λ increases all agents' payoffs from a higher minimum action

⁶ An alternative interpretation is that actions represent effort levels.

⁷ The information available to agents resembles the one available to participants in most weakest-link game based lab experiments.

and thus from a more productive equilibrium.⁸

Bounded Rationality and Belief Formation

Following a long line of organizational and strategy literature (e.g., March and Simon, 1958; Cyert and March, 1963; Heath and Staudenmeyer, 2000; Aggarwal, Siggelkow and Singh, 2011), we assume agents to be boundedly rational. That is, agents are limited forward-looking as they anticipate the effect of sending a message on the other agents' choices in the action phase but ignore that current choices can also affect play far into the future. Agents are also boundedly rational in that they may occasionally make mistakes, or experiment with play that is not optimal. Below, we show results both with and without mistakes and experiments.

One core feature of the weakest-link game is that low-effort beliefs about others' intended actions lead to low actions and hence are self-fulfilling. As a result, the way in which agents form beliefs in our framework is of great consequence. We assume that beliefs can be represented by probabilities, and denote an agent's subjective probability that action a will be the minimum action chosen by all agents when she sends message m as $q(a, m) \geq 0$. In the action phase, $p(a) \geq 0$ is the corresponding probability that action $a \in A$ will be the minimum action chosen by the other agents. We make three substantive modeling choices about the formation of these beliefs:

1. To keep our model tractable, we assume homogeneity in the way in which our agents derive their beliefs. That is, agents interpret the history of play in the same way, and update their beliefs in the same manner.⁹
2. (Communication phase) No communication is interpreted as support for the status

⁸ Most lab experiments using the weakest-link game use two incentive parameters, α and β (with $\alpha > \beta > 0$), and a payoff function equal to $\alpha \underline{a} - \beta a_i - c(m)$ (e.g., Kriss, Blume and Weber, 2016). We prefer our formulation with $\lambda = \alpha/\beta$ as it embodies the equivalent incentives and yields simpler expressions. Note that the level of message costs is only high or low in relation to the incentive parameters.

⁹ Homogenous belief formation is a common assumption in many game-theoretic models. Here, since agents share the history of the game and payoff function, they also share beliefs and derive the same optimal choices. Note that we do not assume that agents know that they are homogenous, or that the details of the decision-making process are common knowledge.

quo in the following situations: Suppose that all agents sent messages indicating the minimum action, or that all agents chose not to communicate, in the previous period. Then the agents believe that either sending a message in the current period that indicates the previous period's minimum action or not communicating will result in the same minimum action also in the current period. Should an agent in either of these two situations instead choose to indicate another action than the previous period's minimum, then this action is believed to have a positive probability (denoted π) of being the new minimum action, while the only other action with a positive probability is the previous period's minimum. The implication of the positive probability is that agents do not rule out communication as ineffective. Formally, if $\mathbf{m}^{-1} = (\underline{a}^{-1}, \dots, \underline{a}^{-1})$ or $\mathbf{m}^{-1} = (\emptyset, \dots, \emptyset)$, then $q(\underline{a}^{-1}, \emptyset) = q(\underline{a}^{-1}, \underline{a}^{-1}) = 1$. Further, $q(a, a) \equiv \pi > 0$, $\forall a \in A \setminus \{\underline{a}^{-1}\}$ and $q(\underline{a}^{-1}, a) = 1 - \pi$.¹⁰

3. (Action phase) If all agents send (and hence receive) identical messages then the agents will choose that sole indicated action. Similarly, if all agents send the empty message, then this is again interpreted as supporting the previous period's minimum action.¹¹ Should one agent send a message indicating a different action than the minimum of the previous period, then there is a chance (again denoted π) that this action becomes the new minimum. Formally, if $\mathbf{m} = (a, \dots, a)$, then $p(a) = 1$. If $\mathbf{m} = (\emptyset, \dots, \emptyset)$, then $p(\underline{a}^{-1}) = 1$. For $a \neq \underline{a}^{-1}$, if $\mathbf{m} = (a, \emptyset, \dots, \emptyset)$, then $p(a) = \pi > 0$ and $p(\underline{a}^{-1}) = 1 - \pi$.

These assumptions allow for a large number of ways in which agents can form beliefs and react to messages. Note in particular that we place no restrictions on how agents use information from the history of play or on the interpretation of the empty message in other situations than those described in Conditions 2 and 3. While this generality is a benefit to

¹⁰ Play in the previous round is marked with superscript -1 .

¹¹ This assumption is analogous to other learning models with boundedly rational agents where agents' beliefs are based on the empirical frequencies of past play (e.g., Young, 1993; Kandori, Mailath and Rob, 1993; Robles, 1997). It also appears in learning models with fully rational agents, e.g., in fictitious play (Fudenberg and Levine, 2009). Our results are however also qualitatively similar when relaxing this assumption by allowing for small positive subjective probabilities for actions that are not indicated by messages or the previous minimum action (results available upon request).

the model, our later simulations will require a more definite formulation of beliefs.

We assume that beliefs respond to single messages indicating a different action than the previous period's minimum in the same way in both phases; that is, π is the same. It seems reasonable that agents are consistent in how they form their beliefs in the two phases, particularly in the long run. Furthermore, allowing π to vary between the action and communication phases does not lead to results that add any intuition about why communication may or may not help team coordination, but it complicates the analysis (such results are available on request).

Next, we present our analytical results. We start by discussing agents' optimal responses in the communication and action phases of the stage game. We then introduce the concepts of absorbing and stochastically stable states — the states where we are most likely to find the team — as solution concepts that help us determine long run outcomes.

Optimal Responses in the Stage-Game

In the communication phase of the stage game, the optimal message is determined by estimating play in the action phase. We formulate an agent's expected utility of sending message m and then choosing action a as $\mathbb{E}u(a, m) = \lambda \sum_{b \in A} q(b, m) \min\{a, b\} - a - c(m)$. Incorporating that a is chosen optimally given m , her indirect expected utility is then $\mathbb{E}v(m) = \max_{a \in A} \mathbb{E}u(a, m)$. She hence chooses a message to maximize $\mathbb{E}v$. Second, in the action phase, her expected utility of choosing action a is $\mathbb{E}u(a) = \lambda \sum_{b \in A} p(b) \min\{a, b\} - a$. She hence chooses an action to maximize $\mathbb{E}u$. Note that in the action phase, incurred message costs are sunk and irrelevant for the choice of action.

For simplicity, but inconsequential to our main results, we assume that ties in the communication stage are broken in favor of communicating, and then in favor of higher-ranked messages. Likewise, in the action phase, ties are broken in favor of higher-ranked actions.

Long-Run Outcomes

Play in any round of the stage game is described by a vector of messages \mathbf{m} and actions

\mathbf{a} that we refer to as a state: $\omega = \langle \mathbf{m}, \mathbf{a} \rangle \in M^N \times A^N \equiv \Omega$. For $a \in A$, let $\omega_a = \langle (\emptyset, \dots, \emptyset), (a, \dots, a) \rangle \in \Omega$, and for $m \neq \emptyset$, let $\omega_{ma} = \langle (m, \dots, m), (a, \dots, a) \rangle \in \Omega$. Let $\Omega^C = \{\omega_a \mid a \in A\}$ be *coordinated states*. Any state $\omega \in \Omega$ transitions into state $T(\omega) \in \Omega$ through optimal play; that is, when all agents play their best responses and do not make mistakes or experiments. Fixed points of T are states that “best respond to themselves”; they are “absorbing”. Let $\Omega^A = \{\omega \in \Omega \mid T(\omega) = \omega\}$ be called the *absorbing states*.

In the appendix, we first show that all absorbing states are also coordinated, $\Omega^A \subseteq \Omega^C$. Furthermore, ω_K is always absorbing, and any state transitions into an absorbing state in a finite number of transitions. Next, we show that the set of absorbing states has a specific structure. Namely, there is a lowest-ranked coordinated state $\omega_\ell \in \Omega^C$ that is absorbing as are all higher-ranked coordinated states: $\Omega^A = \{\omega_\ell, \dots, \omega_K\}$. These results are summarized in Theorem 1. We provide all proofs in the appendix.

Theorem 1. *The set of absorbing states is described as follows.*

1. If $(K-1)(\lambda\pi-1) < \gamma$, then all coordinated states are absorbing: $\Omega^A = \Omega^C$.
2. If $\lambda\pi-1 < \gamma \leq (K-1)(\lambda\pi-1)$, then $\Omega^A = \{\omega_\ell, \dots, \omega_K\}$ for $\ell = \lfloor K - \frac{\gamma}{\lambda\pi-1} + 1 \rfloor$.¹²
3. If $\lambda\pi-1 \geq \gamma$, then ω_K is the unique absorbing state: $\Omega^A = \{\omega_K\}$.

Theorem 1 shows the potential of communication to improve efficiency: If the cost of sending a message (γ) is not too high in relation to incentives (λ) and beliefs (π), then the least efficient coordinated states are not absorbing, and thus not a long-run outcome of the game. In particular, if the incentives and beliefs of agents’ that a message will sway the others are high enough, then the most efficient state in which everyone plays K is the only absorbing state.

Note that by the definition of absorbing states, the only way to break out of one is if an agent makes a mistake or experiments with messages and actions that are not best replies. In practice, efficiency may increase if team members occasionally experiment by, for example, sending a message indicating the highest action in the communication stage to unsettle a

¹² $\lfloor x \rfloor$ denotes the greatest integer not larger than x .

team stuck in an inefficient state. On the other hand, mistakes may also cause a previously efficient team to fail. Our model formalizes mistakes and experiments in the following way: Agents choose a best response message or action according to the above procedure with probability $1 - \epsilon$, and with a small non-zero probability ϵ chooses a message or action by randomizing uniformly between them.¹³

To derive results when mistakes and experiments are possible we use a solution concept that builds on the idea that some absorbing states are easier to transition into than others, in the sense that the transition requires fewer mistakes. Let a state be called *stochastically stable* if — among all the absorbing states — it requires the fewest mistakes to move into this state.¹⁴ Let $\Omega^S \subseteq \Omega^A$ denote the stochastically stable states.

Moving from a higher-ranked to a lower-ranked absorbing state requires only one mistake in the weakest-link game, namely, that an agent chooses the lower-ranked action in the action phase. Thus, moving “down” is always easy, and hence we can reach the lowest-ranked absorbing state ω_ℓ in a single mistake. Therefore, ω_ℓ is always stochastically stable. In contrast, moving “up” through mistakes in the action phase is hard: it often requires *all* agents to make mistakes simultaneously. However, with certain combinations of beliefs and message costs, all that is needed is again just a single mistake in the communication phase. When message costs are high enough so that not communicating is a best response, but one agent sends a message by mistake and messages are influential enough in the action stage,

¹³We use the uniform distribution here for simplicity but relax this restriction and analyze efficiency changes also for other distributions (e.g., experiments that always send the highest message) in the simulation section. See Bergin and Lipman (1996), van Damme and Weibull (2002), and Blume (2003), for discussions about this assumption and when it is appropriate. In our simulations, we further allow ϵ to vary between the communication and action stages.

¹⁴ Alternatively, we could use the solution concept for stochastic stability developed by Foster and Young (1990), Kandori, Mailath and Rob (1993), and Young (1993), and further discussed in Young (1998) and Ellison (2000). Using this alternative solution concept yields the same results for Theorem 2; as their concept is considerably more complex, we prefer to use our simpler one.

play can also transition with a single mistake into higher-ranked absorbing states.

Theorem 2. *The set of stochastically stable states is described as follows.*

1. *If $\lambda\pi - 1 < 0$, then ω_1 is the unique stochastically stable state: $\Omega^S = \{\omega_1\}$.*
2. *If $\lambda\pi - 1 \geq 0$, then all absorbing states are stochastically stable: $\Omega^S = \Omega^A$.*

Similar to our first theorem, Theorem 2 indicates that voluntary communication may enhance long-run efficiency. If we keep the model exactly the same but disallow communication, it is straightforward to show that the least efficient state, ω_1 , is the unique stochastically stable state regardless of the parameters.¹⁵ With voluntary communication, other states are possible long-run outcomes, and if condition 3 in Theorem 1 holds (which implies condition 2 in Theorem 2), then the efficient absorbing state ω_K is the unique stochastically stable state.

Theorem 2 is however more pessimistic about the potential of communication to improve efficiency. For a large range of parameters, the least efficient absorbing state is the only stochastically stable one, and thus the state in which we would expect to find teams most of the time. In particular, with the incentive strength typically used in lab experiments of the weakest-link game — e.g., the implied λ in Kriss, Blume and Weber (2016) is 2 — π must be 0.5 or higher to avoid the least efficient state. It seems unlikely that agents would believe that the chance of a single message persuading all other agents to change their actions was 50 percent or more, even in relatively small groups.

While offering a theoretical benefit, practically, mistakes and experiments seem likely to worsen the potential for communication to solve team coordination problems, but the results above also suggest that they play a different role in the communication and the action phases. It is also evident from Theorem 1 and 2 that for a large range of beliefs, the exact level of message costs is not important. For example, if $\lambda\pi - 1 < 0$, then the least efficient state is

¹⁵ See Robles (1997) or Riedl, Rohde and Strobel (2012) for similar results in models without communication. While this result is in line with much of the experimental evidence for larger groups, it holds regardless of the number of players and the incentives to choose the payoff-dominant action. This seems intuitively less convincing and two-player experimental groups often manage to achieve efficient coordination (Van Huyck, Battalio and Beil, 1990; Camerer, 2003).

stochastically stable regardless of the level of message costs γ — as long as there is a cost.

Communication routines

Theorem 2 indicate that voluntary communication is not enough to create efficient team coordination in many situations. This section explores simple communication routines that may improve efficiency. We focus on the case where mistakes and experiments are possible, as this seems the most plausible scenario both in the lab and in the field.

Proposition 1 states that making communication mandatory, or fully compensating agents for their communication costs (conceptualized by setting $\gamma = 0$), makes the team coordinate on the highest ranked action.

Proposition 1. *If communication is mandatory or fully compensated, then the unique stochastically stable state is $\omega_{KK} = \langle K, \dots, K, K, \dots, K \rangle$.*

The intuition for this result is that once abstaining from communication is not an option, or message costs cease to matter because agents are fully compensated, the trade-off between lowering the strategic uncertainty for the group and costs of sending messages that exists when communication is voluntary disappears. This finding is in line with the experimental results of Blume and Ortmann (2007) and Kriss, Blume and Weber (2016), in which a pronounced majority of players both indicate by message and subsequently choose the highest ranked action when messages are mandatory or costless.

An alternative way to coordinate agents is to elevate a single agent to become the team leader. We model the *team leader* routine in a similar way as in the experiments of Cartwright, Gillet and Van Vugt (2013), Dong, Montero and Possajennikov (2017), and Sahin, Eckel and Komai (2015): let agent 1 be the team leader and let the communication stage consist of agent 1 sending a message while no other agent can communicate. We use the same conditions on beliefs as before; in the communication phase, π now represents the team leader’s belief that a message will change other team members decisions about which actions to take. In the action phase, π represents the subjective probability placed by all

agents that the action indicated by the team leader will be the minimum action.

Prior lab experiments have varied the routine in two ways: in one, the team leader can voluntarily choose whether or not to communicate. This is very similar to our voluntary communication situation, except that only the team leader can communicate. In the second, the team leader is “leading by example” by being the first to choose an action which is communicated to the rest of the team. The latter translates naturally to our model by forcing the team leader to communicate as well as to choose the action that he/she has indicated by message.

Our model predicts that the two versions of the routine will end up having a very similar effect. The only substantive difference is that the leading by example routine has just two possible stochastically stable states — either the team coordinates on the least efficient or on the most efficient state. The reason is that the routine forces the team leader to communicate. Unlike the mandatory communication routine, which also forces communication, leading by example does not necessarily lead to the most efficient outcome. The cost of a potential mismatch between a sent message and the minimum action chosen by the other agents explains the difference.

Proposition 2. *With communication restricted to a team leader that either 1. can communicate voluntarily, or 2. leads by example, the stochastically stable states are*

1. *If $\lambda\pi - 1 < 0$, then ω_1 is the unique stochastically stable state. If $0 \leq \lambda\pi - 1 < \gamma$, then the stochastically stable states are $\Omega^S = \{\omega_\ell, \dots, \omega_K\}$ for $\ell = \lfloor K - \frac{\gamma}{\lambda\pi - 1} + 1 \rfloor$. If $\lambda\pi - 1 \geq \gamma$, then ω_K is the unique stochastically stable state.*
2. *If $\lambda\pi - 1 < 0$, then $\omega = \langle 1, \emptyset, \dots, \emptyset, 1, \dots, 1 \rangle$ is the unique stochastically stable state. If $\lambda\pi - 1 \geq 0$, then $\omega = \langle K, \emptyset, \dots, \emptyset, K, \dots, K \rangle$ is the unique stochastically stable state.*

Proposition 2 is in line with the results of the three lab experiments. Sahin, Eckel and Komai (2015) investigate two team leader routines: one leader, who leads by example, and one who communicates an action to the team before everyone takes action (but the

leader does not have to follow his/her own suggestion). Both routines substantially improve outcomes in the weakest-link game, but are not significantly different from one another. Dong, Montero and Possajennikov (2017) examine the same two routines, but find that neither leading by example, nor pre-action communication by the team leader is enough to escape coordination failure, although teams do slightly better under both routines than in a no-communication treatment. The difference between the two experiments lies primarily in the incentive structure as the incentives are weaker in Dong, Montero and Possajennikov (2017).¹⁶ Cartwright, Gillet and Van Vugt (2013) examine only leading by example, and occupy a middle ground in the game’s parameters. They find a clear improvement over the no-communication benchmark, but only few teams coordinate on the efficient equilibrium.

Our model suggests that having a team leader may improve efficiency compared to allowing voluntary communication for the whole team, if the team leader’s own expectations are high enough and the team leader has enough authority or credibility; that is, if π is higher with than without a team leader. There are no experiments varying team leader authority or credibility that exactly match our set up, but credibility influences the impact of communication in the weakest-link experiments of Brandts, Cooper and Weber (2014) and Kriss and Eil (2012). In the latter study, expectations are also shown to be important for efficiency: team leaders sometimes fail to use costly communication that would help their groups.

Our model predicts long-term outcomes. In many organizational settings, team members do not work with each other for extended time periods but are instead called upon from different business units to serve for specific functions and for a short work spell only. Likewise, lab experiments on team efficiency are usually performed for only a restricted number of rounds (typically 8-12). Our model outcomes may hence differ from organizational and lab outcomes as teams may not yet have arrived at their equilibrium when their work spell ends. To further facilitate the comparison of our model to short-run results from the lab and the field, we therefore run simulations of our model in the next section. Besides establishing

¹⁶ Dong, Montero and Possajennikov (2017) use groups of four, and Sahin, Eckel and Komai (2015) groups of six, suggesting that the incentives are more important in these short-run cases.

the short-run results of our model, this exercise allows us try out new routines with mandatory communication in some early rounds of the game. Such routines would not change the outcome in the very long-run but may be important for short-run team coordination. Furthermore, we can also examine the effect of team size and test the results' sensitivity to relaxing some of the assumptions.

SIMULATION

We start by discussing the version of the model used in the simulation. We then describe the simulation setup, the way in which we relax some of the prior assumptions, and its results. Lastly, we examine the model at a more general level and relate it to experimental results.

Simulation model

The three conditions on agents' belief formation admit a large number of ways in which agents can form beliefs and react to messages. To run simulations, we require a more precise functional form for how agents reason about how a message will affect other agents and how agents react to messages. We strive for a simple formulation and therefore let agents use the empirical frequencies of prior signals indicating action a in both the communication and action phases.¹⁷ This then leads to the following functional forms of the beliefs first introduced on page 8.

Communication stage: Let $q_{ij}(a, m)$ denote i 's expectation over j 's subjective probability of action a becoming the minimum in period $t > 1$ in case i sent message m . Formally, using the empirical frequency of prior messages, this gives $q_{ij}(a, m) = \frac{1}{N} \left(\mathbf{1}(m = a) + \sum_{j \in I \setminus \{i\}} \mathbf{1}(m_j^{-1} = a) + |\emptyset| \times \mathbf{1}(\underline{a}^{-1} = a) \right)$.¹⁸ Unless agent i contemplates to

¹⁷ Using empirical frequencies of past play also occurs in learning models by Young (1993); Kandori, Mailath and Rob (1993); Robles (1997) and Fudenberg and Levine (2009).

¹⁸ $\mathbf{1}(\cdot)$ is the indicator function equal to 1 whenever the condition in parentheses holds. Note that this formulation constrains $\sum_{a=1}^K q_{ij}(a, m)$ to be 1 for each $m \in M$, except for during the initial period when there are no messages from a prior stage. In the initial period, we uniformly randomize a vector of non-empty messages.

make a change from communication to no-communication or the other way around, the term $|\emptyset|$ is just the number of empty messages sent in the previous period. If i does contemplate a change from sending a substantive to the empty message (or from the empty to a substantive message), $|\emptyset|$ decreases (increases) by one.

Action stage: Next, in the action stage, agent i chooses $a \in A$ in order to maximize her expected utility $\mathbb{E}u_i(a)$. Let agent i 's expectation over agent j playing action a be denoted $p_{ij}(a)$. This expectation is again determined by whether the action has been indicated by messages, or indicated by the combination of the empty message and being the minimum action in the previous period. Put formally, if $m_j = a$ or ($m_j = \emptyset$ and $\underline{a}^{-1} = a$) then $p_{ij}(a) = 1$, else 0. Agent i then use the frequency by which an action has been indicated to derive the subjective probability of $a \in A$ to be the minimum action as: $p_i(a) = \frac{1}{N} \sum_{j \in I} p_{ij}(a)$. Having done that for all actions, agent i then uses $p_i(a)$ to compute, for each possible action a , her expected utility $\mathbb{E}u_i(a) = \lambda \sum_{b \in A} p_i(b) \min\{a, b\} - a$, and subsequently chooses the action that maximizes her expected payoff.

Simulation setup

To facilitate the comparison of our results to those from the lab, our simulation uses eight periods of play in each parameter configuration (the same as in, e.g., Kriss, Blume and Weber (2016)). Weakest-link games in the lab typically set incentives as $\lambda = 2$.¹⁹ We therefore let λ vary around this midpoint, $\lambda \in \{\frac{20}{12}, \frac{20}{11}, \frac{20}{10}, \frac{20}{9}, \frac{20}{8}\}$. We further allow the number of agents and the number of actions to vary between 2 and 10 (in increments of two) and the level of message costs to vary between 1 and 9 (in increments of two).

We introduce three levels of mistake/experiment probabilities in the communication and action stages — 0, 10, and 20 percent — and, relaxing an earlier model assumption, let those probabilities differ between the communication and action stages.²⁰ We repeat configurations

¹⁹ Recall that $\lambda = \alpha/\beta$ when writing the payoff function as $\alpha \underline{a} - \beta a_i - c(m)$. A lower β (higher λ) increases the incentives to choose a higher ranked action. Most weakest-link games in the lab use $\alpha = 20$ and $\beta = 10$.

²⁰ The experimental literature examining the relationship between stated beliefs and strategic choices

with non-zero probabilities for mistakes or experiments in our simulation 100 times, and use the average of these configurations in the tests below.

The earlier modeling choice to use a uniform distribution to determine a new message or action when a mistake or experiment occurs need not be innocuous, as discussed by Bergin and Lipman (1996) and van Damme and Weibull (2002). For example, agents may be intentionally experimenting with higher messages and may prefer to do so in the communication rather than the action stage as the potential payoff loss of trying higher ranked actions is much greater than of trying higher ranked messages. Consistent with this, the highest ranked message is (by a wide margin) also the most common non-empty message in the lab experiment of Kriss, Blume and Weber (2016). Alternatively, unintentional mistakes should affect both the communication and action stages and not emphasize any message other than, perhaps, the intended one.

We therefore extend our analysis to repeat all simulations using four alternative distributions for mistakes and experiments: First, as in the analysis of the long-run, we use a uniform distribution such that — if a mistake or experiment occurs — each message or action is equally likely to be played, as it may be the case for an unintentional slip-up. Second, we use a distribution that is centered on the intended message or action but that has also non-zero probabilities for surrounding realizations: in this distribution (henceforth abbreviated as *DoubleDist*), the probability for any surrounding action or message halves as the distance from the intended one doubles. This relates to the idea of inattention affecting an agent’s communication or action, leading to a choice that is similar yet distinct from the intended one. Third, motivated by observations in the lab, another distribution (abbreviated as *HighestMsg*) captures intentional experiments and puts all weight on the highest ranked message. Finally, we use a distribution (abbreviated as *Exponential*) in which higher ranked messages become increasingly more likely, formalized via an (inverted) Exponential distri-

often find frequencies of choices that are not best reply responses to stated beliefs at least as high as these probabilities (e.g Nyarko and Schotter, 2002; Costa-Gomes and Weizsäcker, 2008; Manski and Neri, 2013).

bution with a rate parameter of 1 and rescaled to cumulate to 100 percent.²¹ With some positive support also on some lower-ranked messages, this occupies middle ground between unintentional mistakes and intentional experimenting.

We also expand the range of communication routines in our simulation by adding routines that mandate communication only for the first period, or for the first two periods. Those communication protocols are a blend of the complete mandatory and complete voluntary communication protocols examined in the model section and may be in line with managerial attempts to enforce a greater level of communication in the early days of a team.²²

The above parameter ranges and choice of distributions yield 135,000 distinct configurations and — when adding the 100 simulations for each configuration with non-zero mistake probabilities — over 11 million simulations.

Simulation Results

We start by comparing our model and its simulation results to findings from an experimental study that is close in its setup to ours, namely that of Kriss, Blume and Weber (2016). Since experiments in the lab use specific parameters for incentives, group sizes, messaging costs and number of rounds, we then proceed to discuss our simulation output for a wider parameter range. We also describe the changes in coordination outcomes when introducing specific team communication routines.

Comparison to experimental results

Kriss, Blume and Weber (2016) use incentive parameters α and β equal to 20 and 10 ($\lambda = 2$ in our formulation), 9 agents, 7 actions and 8 rounds. Further, the authors vary message costs across two treatments and set them equal to either 1 or 5. In Figure 2 we show the empirical distributions of minimum actions in round 8 of our simulations when limiting the

²¹ That is, $Pr(x) = 1/(\gamma \exp(-\gamma x))$ with $\gamma = 1$ and then rescaled to sum up to 100 percent for all messages. For example, in the case of seven messages, the probabilities for messages 1 to 7 (should an experiment or mistake occur) are respectively 0.2%, 0.4%, 1.2%, 3.2%, 8.6%, 23.3% and 63.3%.

²² We thank Peter Kriss for suggesting these routines.

number of agents, actions and message costs to those in the experiment, and when allowing for non-zero mistake probabilities in both the communication and action stages. We show results separately for the four mistake distributions of the communication stage.

Figure 2 shows that all seven actions are represented among the minimum actions, but it is clear that in all specifications the lowest action is the most frequent outcome for the minimum action of round 8. Note also that the distributions are very similar regardless of the level of message costs — this matches the experimental finding by Kriss, Blume and Weber that a large change in messaging costs is not enough to fully induce coordination on the efficient outcome.²³

[INSERT FIGURE 1 ABOUT HERE]

Table 1 contains the means and standard deviations for the minimum action in round 8 of the simulations. Notably, comparing results across rows shows that a reduction in the likelihood of large mistakes in the action stage (that is, moving from a *Uniform* to a *DoubleDist* mistake distribution in the action stage) improves average outcomes in the final stage. Similarly, mistake distributions that allow for a greater number of high experiments in the communication stage (*HighestMsg* and *Exponential*) also improve final-round outcomes. Comparing those results to Kriss, Blume and Weber, under low messaging costs of 1 in the lab, the average minimum action in round 8 is 2.75. This lies firmly within the range of the simulated outcomes across the mistake distributions whose averages range from 1.66 to 3.36. As our averages are however very similar for message costs equal to 5, those are further away from the experimental mean where all six groups end up with a minimum action of 1 in round 8. The simulation results in Table 1 reflect a feature also seen in the analytical solution to the model and confirmed in the results that use a wider range of parameters (see

²³ In their treatment with message costs equal to 5, all six of their groups have a minimum action of 1 in the final round. When message costs are reduced to 1, four groups (or 50 percent of the eight groups in the second treatment) still end up with action 1, two more groups (or 25 percent) end with action 3, and one group each (12.5 percent) end with action 5 and action 7. This is not unlike our simulation results in which agents are more likely to experiment with higher ranked messages in Panels C and D: averaged across those two distributions, actions 1, 3, 5, 7 are the minimum actions in the final period in 44, 10, 7, and 9 percent of the simulated groups.

next section): With the range of parameters commonly used in experiments, our estimates are not very sensitive to increases in the cost of messages. In summary, we conclude that the simulation results from our model broadly match the experimental results from the lab.

[INSERT TABLE 1 ABOUT HERE]

Results for the full parameter range and alternative communication routines

To be able to separate the effects of individual parameters on the simulated actions in the final round of the game, Table 2 reports the output of an OLS regression that uses the minimum action of the team in the final round of each simulation as the dependent variable.²⁴ Our independent variables include indicator variables for each increment of the variables used to determine the configurations, using the category with the lowest value as the reference category throughout.

[INSERT TABLE 2 ABOUT HERE]

The simulations yield five findings. First, increasing the payoff incentives from coordinating on a higher action (that is, a higher λ) increases the minimum team action in the final period. Second, we would expect that larger groups should make it more difficult to use communication to break out of inefficient states, but to also increase the number of occasions where some agent makes a mistake or experiment to help the group get “unstuck” from a low equilibrium. The first effect should imply lower average minimum actions, while the direction of the second effect should depend on the distribution. We find that larger groups, overall, have greater difficulties to coordinate on high outcomes, with negative coefficients that increase linearly with team size. However, these results occur after controlling for the presence of communication routines, whereas communication is

²⁴ For configurations with positive mistake or experiment probabilities, we use only the average of the final round’s action across the 100 repeated simulations as a single observation. While included, we omit the output for the indicator variables for the different number of actions, as - unsurprisingly - the magnitude of the final round action increases mechanically when more actions are available.

most advantageous for coordination in larger teams. We further explore below the interplay between communication routines and group size.

Third, similar to the long-run analytical results, differences in message costs — unless very high — seem to not matter to the final outcome in the short-run: while costless communication allows for efficient coordination, we find no differences when message costs range between 1 and 7. Hence, even message costs as small as 1 entail private costs from communication that overwhelm the expected benefit from being able to sway colleagues’ actions.

Fourth, the coefficients on the probability of mistakes or experiments in the action stage are large and negative, with a larger probability reducing minimum actions by more. This unequivocally shows that experimenting in the action stage is detrimental to team coordination. In contrast, mistakes and experiments in the communication stage have a positive influence on final team outcomes, with larger probabilities having also a larger positive impact.

Compared to the uniform distribution (the omitted category in the regression), using the *DoubleDist* mistake distribution in the action stage makes it less likely that play drops all the way to a lower ranked action by just one mistake. This is sensible since any mistake tends to be closer to the intended action than under the uniform distribution where a far lower action played by mistake is quickly followed by far lower play of other agents. On the other hand, in the communication stage, the *DoubleDist* distribution makes it less likely that a mistaken message indicates a much higher ranked action than the intended one; as a result, it is also less helpful in elevating the group’s action once it becomes “stuck” at a lower equilibrium. Further, experimentation with higher messages in the communication stage under the *HighestMsg* and *Exponential* distributions increase the minimum action in the final period.

Finally, making communication mandatory in the first round increases the minimum action in the final period. Adding a second round of initial mandatory communication yields a further increase in the final outcome. Yet, at first glance, the short-run effect seems fairly

modest when compared to potential gains from changing the incentives to coordinate, or from reducing team size.

Team size ranks among the greatest determinants of coordination but is often pre-determined by the size of the task or the diversity of skills required for the task. For example, manpower needed in security and safety services or for data collection scales proportionally to the size of the task, and product development may require a certain number of workers with specialized skills from different business units. We are therefore interested in how team size affects the effectiveness of the tested communication routines and experiments.

Table 3 shows output from an OLS regression with the the simulated minimum action in the final round as the dependent variable, and interaction terms of team size with the communication routines, with experiment probabilities and with experiment distributions as independent variables.²⁵ There are two major findings. First, mandating communication in early rounds improves coordination outcomes for all team sizes (rows 1 and 2, column 1) and the effect is not limited to small groups only (interaction terms in columns 2-5 of rows 1 and 2). Second, allowing for experiments to occur in the action phase decreases coordination, and this further worsens as team size grows (rows 3 and 4). In contrast, experiments in the communication phase support efforts to coordinate on higher actions but its effectiveness decreases for larger teams (rows 5 and 6). The coefficients for the experiment distributions corroborate this further: The two distributions that encourage high-messages in the communication stage benefits all the groups, but their benefit decrease again as teams grow in size (rows 7 and 8). As in Table 2, the *DoubleDist* distribution in the communication stage worsens outcomes relative to the uniform distribution but the effect is small in larger teams.

[INSERT TABLE 3 ABOUT HERE]

In sum, our simulations suggest that coordination problems are more serious for larger

²⁵The regression also contains all the other variables shown in Table 2 but their output is suppressed for expositional ease.

teams, and such teams are more unlikely to talk their way out of inefficient equilibria, even if team members are trying to communicate a more efficient course of action. Mandating some communication does help, also when teams are large, but does not solve the coordination problem. The simulations further suggest that organizations should rather target the incentives to coordinate than the costs of communication, as the effect of strengthening the incentives is considerably larger. For the design of lab experiments, it is interesting to note that although coordination problems grow with team size, even teams as small as four subjects are typically unable to coordinate on efficient outcomes. Implementing experiments with smaller groups would enable an increase in the number of teams for the same cost, an important benefit when examining coordination, which is a group level phenomena.

CONCLUDING REMARKS

This article develops a model to examine how costly communication affects team coordination in situations when outcomes are determined by the lowest quality input from any one member. The results imply that efficient coordination is difficult to achieve: for a wide range of parameters, including those used in lab experiments, our model predicts that the least efficient coordinated state is the most likely long-run outcome. The explanation is that communication costs introduce a trade-off for agents between lowering the strategic uncertainty for the team and the private costs of communication. The model has considerable explanatory power also in the short run; the difficulties experienced by experimental subjects to coordinate efficiently when communication is costly is clearly mirrored by our simulations. The coordination problems grow with team size, but even teams as small as four subjects are typically unable to coordinate on efficient outcomes.

These results suggest that organizations may improve the efficiency of teams by reducing the costs of communicating, but short of fully compensating team members for communication costs, such reductions are often not enough to achieve efficient coordination. Targeting the incentives to coordinate and structuring communication by imposing routines may there-

fore be more important and, under certain conditions, necessary for efficient coordination. Making communication mandatory in every round or fully compensating team members for communication costs makes agents coordinate on the action with highest payoff. Using one and two rounds of mandatory communication improves outcomes in the simulations, but does not fully solve the coordination problem in the short run. A team leader may also induce efficient coordination but only when he or she has enough authority or credibility, and expects to be able to persuade the group to choose the communicated action. Finally, encouraging team members to experiment by sending higher messages in the communication stage can raise team outcomes.

Although our model is broadly consistent with recent experimental results, it is of course in some aspects a drastic simplification of human decision-making. Still, we think that the modeling of costly communication is a step towards richer game-theoretical models of organizational coordination; models that allow for more general ways of communication and are informative about how communication routines can be designed to achieve efficient coordination.

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APPENDIX: PROOFS

Theorem 1

The theorem is a corollary to Proposition 4; the two cases are obtained by solving for $\ell \leq 1$ and $\ell \geq K$.

Lemma 1. (*Action phase*) *If there is $a \in A$ such that $p(a) = 1$, then a is optimal.*

Proof. Let $b \in A$. If $a < b$, then $\mathbb{E}u(b) = \lambda a - b < \lambda a - a = \mathbb{E}u(a)$. If $a > b$, then $\mathbb{E}u(b) = \lambda b - b < \mathbb{E}u(a)$. \square

Lemma 2. (*Communication phase*) *If $m \in M$ is optimal, then there is $a \in A$ such that $\mathbb{E}v(m) = \mathbb{E}u(a, m)$ and $q(a, m) > 0$.*

Proof. To obtain a contradiction, suppose that $q(a, m) = 0$. If $a = 1$, then $\mathbb{E}u(a + 1, m) = \mathbb{E}u(a, m) + \lambda - 1 > \mathbb{E}u(a, m)$, so $\mathbb{E}v(m) > \mathbb{E}u(a, m)$. We derive the same contradiction if $a = K$: then $\mathbb{E}u(a - 1, m) = \mathbb{E}u(a, m) + 1 > \mathbb{E}u(a, m)$. For $1 < a < K$,

$$\begin{aligned} \mathbb{E}u(a, m) - \mathbb{E}u(a - 1, m) &= \lambda \sum_{b \in A} q(b, m) (\min\{a, b\} - \min\{a - 1, b\}) - (a - (a - 1)) \\ &= \lambda \sum_{b < a} q(b, m)(b - b) + \lambda \sum_{b \geq a} q(b, m)(a - (a - 1)) - 1 \\ &= \lambda \sum_{b \geq a} q(b, m) - 1 = \lambda \sum_{b \geq a+1} q(b, m) - 1 = \mathbb{E}u(a + 1, m) - \mathbb{E}u(a, m). \end{aligned}$$

The final equality is derived along the same lines as the first ones. Hence, $\mathbb{E}u(a, m) \geq \mathbb{E}u(a - 1, m) \iff \mathbb{E}u(a + 1, m) \geq \mathbb{E}u(a, m)$. If equality, then the tie is broken in favor of $a + 1$. \square

Lemma 3. *Let $\underline{a}^{-1} = a$ and $\mathbf{m}^{-1} = (a, \dots, a)$. If message m is optimal, then $\mathbb{E}v(m) = \mathbb{E}u(m, m)$.*

Proof. By Lemma 2, the action $b \in A$ that is optimal having sent m has positive probability: $q(b, m) > 0$. Hence, $b \in \{a, m\}$. If $m = a$, then $b = m$, so $\mathbb{E}v(m) = \mathbb{E}u(m, m)$. If $b = a \neq m$, then sending \emptyset is better, contradicting that m is optimal: $\mathbb{E}v(m) = \mathbb{E}u(a, m) = \mathbb{E}u(a, \emptyset) - \gamma < \mathbb{E}u(a, \emptyset)$. Hence, $b \neq a$, so $b = m$. \square

Proposition 3. *Absorbing states are coordinated, $\Omega^A \subseteq \Omega^C$.*

Proof. Starting from an arbitrary $\omega \in \Omega$, we show that the possible transitions are as in Figure 1. A state is absorbing if it loops back to itself. A consequence is that ω_K always is absorbing, and that any state transitions into an absorbing state in a finite number of transitions.

Part 1: For $\omega \in \Omega$, $T(\omega) = \omega_{aa}$ for some $a \in A$ or $T(\omega) = \omega_{\underline{a}-1}$.

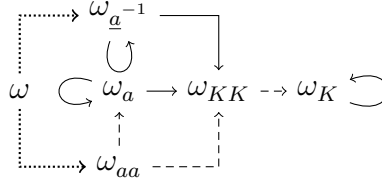


Figure 1: Dotted lines refer to Part 1. Dashed lines refer to Part 2. Remaining lines refer to Part 3.

By condition 1, all agents derive the same optimal message $m \in M$. Let $a = m$ if $m \neq \emptyset$ and $a = \underline{a}^{-1}$ otherwise. By condition 3, $p(a) = 1$ in both cases. By Lemma 1, all agents choose a . Hence, $T(\omega) = \omega_{aa}$ or $T(\omega) = \omega_{\underline{a}^{-1}}$.

Part 2: For $a \in A$, $T(\omega_{aa}) = \omega_a$ or $T(\omega_{aa}) = \omega_{KK}$.

First, suppose that the agent abstains from communicating. By condition 2, $q(a, \emptyset) = 1$. By Lemma 2, $\mathbb{E}v(\emptyset) = \mathbb{E}u(a, \emptyset) = (\lambda - 1)a$. Second, suppose that the agent sends message $m \neq \emptyset$. By condition 2, $q(m, m) = \pi$ and $q(a, m) = 1 - \pi$. By Lemma 3, $\mathbb{E}v(m) = \mathbb{E}u(m, m) = \lambda(\pi m + (1 - \pi)\min\{a, m\}) - m - \gamma$. Message $m \leq a$ is not optimal: $\mathbb{E}v(m) = (\lambda - 1)m - \gamma < (\lambda - 1)a = \mathbb{E}v(\emptyset)$. Therefore, $T(\omega_{KK}) = \omega_K$. For $a < K$ and $m > a$:

$$\mathbb{E}v(m) = \lambda(\pi m + (1 - \pi)a) - m - \gamma = (\lambda\pi - 1)m + \lambda(1 - \pi)a - \gamma = (\lambda\pi - 1)m + \mathbb{E}v(\emptyset) - \gamma.$$

For m to be optimal, $\mathbb{E}v(m) \geq \mathbb{E}v(\emptyset)$, so $\lambda\pi - 1 > 0$. But then $\mathbb{E}v$ is increasing in m , so $m = K$ is optimal. Hence, $T(\omega_{aa}) = \omega_a$ or $T(\omega_{aa}) = \omega_{KK}$.

Part 3: For $a \in A$, $T(\omega_a) = \omega_a$ or $T(\omega_a) = \omega_{KK}$.

This is solved as ω_{aa} in Part 2. □

Proposition 4. *There is $\ell \in A$ such that $\Omega^A = \{\omega_\ell, \dots, \omega_K\}$.*

Proof. Suppose that $\omega_a \in \Omega^C$ was played in the previous round. By Lemma 3, $\mathbb{E}v(a) = \mathbb{E}u(a, a)$ and $\mathbb{E}v(K) = \mathbb{E}u(K, K)$. By Part 3 of the proof of Proposition 3, $T(\omega_a) = \omega_a$ or $T(\omega_a) = \omega_{KK}$. Hence, ω_a is absorbing whenever $\mathbb{E}v(a) > \mathbb{E}v(K)$:

$$\mathbb{E}v(a) - \mathbb{E}v(K) = (\lambda - 1)a - [\lambda(\pi K + (1 - \pi)a) - K - \gamma] = (\lambda\pi - 1)(a - K) + \gamma. \quad (\star)$$

If $\lambda\pi - 1 \leq 0$, then \star is positive for each $a \in A$, so each ω_a is absorbing. Thus, $\Omega^C = \Omega^A$ and $\ell = 1$. If $\lambda\pi - 1 > 0$, then \star is increasing in a . Therefore, if \star is positive for a , so ω_a is absorbing, then \star is positive for $a + 1$, so ω_{a+1} is absorbing. This yields the desired structure

on Ω^A . Let $\omega_\ell \in \Omega^A$ and $\omega_{\ell-1} \notin \Omega^A$. Then

$$\begin{aligned} (\lambda\pi - 1)(\ell - 1 - K) + \gamma \leq 0 < (\lambda\pi - 1)(\ell - K) + \gamma &\iff \ell - 1 \leq K - \frac{\gamma}{\lambda\pi - 1} < \ell \\ &\iff \ell = \lfloor K - \frac{\gamma}{\lambda\pi - 1} + 1 \rfloor. \quad \square \end{aligned}$$

Theorem 2

Proof. The intuition for why moving “down” is easy should be clear enough from the text. All that remains is to check when moving “up” also is easy.

Let $\underline{a}^{-1} = a \in A \setminus \{K\}$ and $m > a$. Suppose that the only (non-empty) message is m , so $\mathbf{m} = (m, \emptyset, \dots, \emptyset)$. Then

$$\mathbb{E}u(m) - \mathbb{E}u(a) = \lambda(\pi m + (1 - \pi)a) - m - (\lambda - 1)a = (\lambda\pi - 1)(m - a).$$

As $m > a$, $\mathbb{E}u(m) \geq \mathbb{E}u(a)$ whenever $\lambda\pi - 1 \geq 0$. In conclusion, suppose that $\lambda\pi - 1 \geq 0$. Starting from $\omega_a \in \Omega^A$, if one agent mistakenly sends message $m > a$, then play transitions into ω_m . Thus, moving up is as easy as moving down, so any absorbing state is reachable from any other in a single mistake. Therefore, all absorbing states are stochastically stable. \square

Proposition 1

Proof. Mandatory communication: Part 2 of Proposition 3 showed that either $m = \emptyset$ or $m = K$ is optimal. Mandatory communication rules out $m = \emptyset$, and therefore $m = K$ is optimal for each agent. If all agents send $m = K$, $a = K$ is the optimal action by Condition 3. Consequently, $\omega_{KK} = \langle K, \dots, K, K, \dots, K \rangle$ is the only absorbing and therefore also the only stochastically stable state.

Fully compensated communication: If $\gamma = 0$, Lemma 1 and 2 still holds. Part 1 of Proposition 3 therefore still holds, so $T(\omega) = \omega_{aa}$ for some $a \in A$ or $T(\omega) = \omega_{\underline{a}^{-1}}$. If the process is in ω_{aa} or $\omega_{\underline{a}^{-1}}$, $m = \emptyset$ is never optimal, as $m \geq a$ yields $\mathbb{E}v(m) = \mathbb{E}u(a, m) \geq \mathbb{E}u(a, \emptyset) - \gamma = \mathbb{E}u(a, \emptyset)$ and ties are broken by sending messages. Furthermore, as $\mathbb{E}u(a, K) \geq \mathbb{E}u(a, m)$ and ties are broken by sending higher ranked messages, $m = K$ is optimal, regardless of π . By Condition 3, when all agents send K , $p(K) = 1$ and all agents choose K . Once in ω_{KK} , K continues to be the optimal message and action by the same reasoning, and is therefore the only absorbing and stochastically stable state. \square

Proposition 2

Proof. Part 1: We start by showing that absorbing states are coordinated when the team leader can voluntarily choose whether to communicate or not. Note that Lemma 1 and 2 holds also when a single agent communicates. Furthermore, a slightly modified version of Lemma 3 also hold: let $\underline{a}^{-1} = a$ and $\mathbf{m}^{-1} = (a, \emptyset, \dots, \emptyset)$. The proof of the statement that if

message m is optimal, then $\mathbb{E}v(m) = \mathbb{E}u(m, m)$ follows the exact same steps laid out in the proof of Lemma 3.

To show that absorbing states are coordinated, assume $\underline{a}^{-1} = a$. The team leader chooses m optimally. First, suppose the team leader contemplates abstaining from communicating. Then $q(a, \emptyset) = 1$. By Lemma 2, $\mathbb{E}v(\emptyset) = \mathbb{E}u(a, \emptyset) = (\lambda - 1)a$. Second, suppose that the team leader contemplates sending message $m \neq \emptyset$. Message $m \leq a$ is not optimal: $\mathbb{E}v(m) = (\lambda - 1)m - \gamma < (\lambda - 1)a = \mathbb{E}v(\emptyset)$. For $m > a$, by Condition 2, $q(m, m) = \pi$ and $q(a, m) = 1 - \pi$. By Lemma 3, $\mathbb{E}v(m) = \mathbb{E}u(m, m) = \lambda(\pi m + (1 - \pi)\min\{a, m\}) - m - \gamma$. For $a < K$ and $m > a$:

$$\mathbb{E}v(m) = \lambda(\pi m + (1 - \pi)a) - m - \gamma = (\lambda\pi - 1)m + \lambda(1 - \pi)a - \gamma = (\lambda\pi - 1)m + \mathbb{E}v(\emptyset) - \gamma.$$

For m to be optimal, $\mathbb{E}v(m) \geq \mathbb{E}v(\emptyset)$, so $\lambda\pi - 1 > 0$. But then $\mathbb{E}v$ is increasing in m , so $m = K$ is optimal. That is, the team leader sends either the empty message or $m = K$, but $m = K$ is never optimal if $\underline{a}^{-1} = K$. This implies that all absorbing states are coordinated. Showing that there is $\ell \in A$ such that $\Omega^A = \{\omega_\ell, \dots, \omega_K\}$ follows by noting that π is the same for all agents by Condition 1 and then Proposition 4 holds for the team leader by the same reasoning as in that proof. This proposition gives us the result in Theorem 1. As the least number of mistakes needed to move from one absorbing state to another is not different with a team leader (i.e., it is always 1), Theorem 2 also holds, which proves the first part of the proposition.

Part 2: The leading by example routine rules out not communicating for the team leader, so absorbing states cannot be coordinated according to our definition, but Lemma 1, 2, and the modified version of Lemma 3 presented above holds. Assume $\underline{a}^{-1} = a$. Then, for m to be optimal, $\mathbb{E}v(m) > \mathbb{E}v(m') \forall m \in A$. Message $m < a$ is not optimal: $\mathbb{E}v(m)$ is at most $(\lambda - 1)m - \gamma < (\lambda - 1)a - \gamma = \mathbb{E}v(a)$. Message $m > a$ is optimal when

$$\mathbb{E}v(m) - \mathbb{E}v(a) = [\lambda(\pi m + (1 - \pi)a) - m - \gamma] - (\lambda - 1)a + \gamma = (\lambda\pi - 1)(m - a) \geq 0.$$

Again, $\mathbb{E}v$ is increasing in m , so $m = K$ is optimal whenever this holds. The inequality does not need to be strict as ties are broken in favor of higher ranked messages. Hence, the team leader either sends a message indicating the previous period's minimum action, or K . The absorbing states are therefore of the types $\omega = \langle a, \emptyset, \dots, \emptyset, a, \dots, a \rangle$. The least number of mistakes needed to move between the absorbing states then follows the the proof of Theorem 2, which proves Part 2. \square

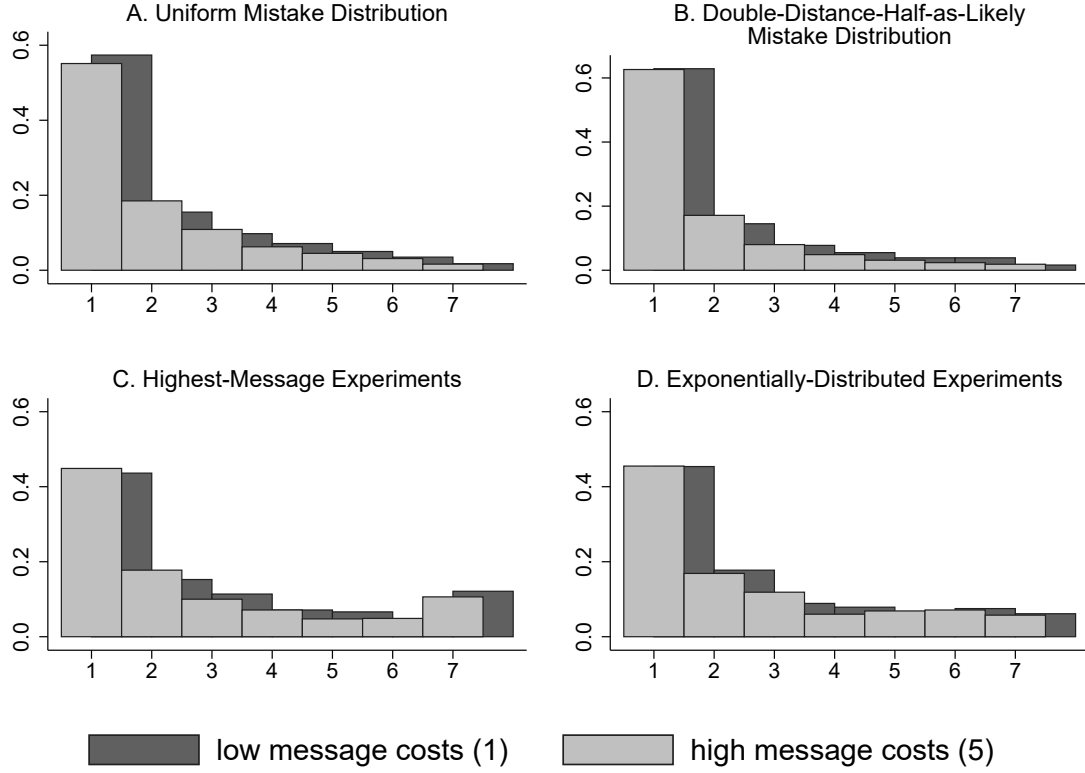


Figure 2: Message costs and mistake distributions

This figure shows the simulated minimum team actions after round 8 when following the lab specification in Kriss, Blume and Weber (2016) ($\lambda = 2$, 9 agents, 7 actions, and message costs either low (1) or high (5)). We show results for simulations with non-zero mistake probabilities in both communication and action stages.

Table 1: Descriptive statistics of final round minimum action

This table displays descriptive statistics of the the final round action in the simulations with eight rounds. With the non-zero mistake probabilities, each minimum action is averaged over 100 repetition of the same configuration. Results are horizontally separated by the mistake probability in the communication stage (*uniform*, *double-distance-half-as-likely*, *highest message* and *exponential*) and vertically separated by the mistake probability in the action stage (*uniform*, *double-distance-half-as-likely*). Panel A shows results when message costs are low (1) and Panel B shows results when message costs are high (5). Shown are the means and the standard deviation in parentheses of the minimum actions in the final round.

Panel A: Low message costs				
Distribution	<i>Uniform</i>	<i>DoubleDist</i>	<i>HighestMsg</i>	<i>Exponential</i>
<i>Uniform</i>	1.74 (0.141)	1.66 (0.043)	2.21 (0.473)	2.16 (0.423)
<i>DoubleDist</i>	2.35 (0.515)	2.16 (0.346)	3.36 (0.839)	3.03 (0.690)
Panel B: High message costs				
Distribution	<i>Uniform</i>	<i>DoubleDist</i>	<i>HighestMsg</i>	<i>Exponential</i>
<i>Uniform</i>	1.70 (0.164)	1.67 (0.114)	2.23 (0.621)	2.17 (0.430)
<i>DoubleDist</i>	2.35 (0.338)	2.00 (0.202)	3.09 (0.727)	2.96 (0.709)

Table 2: Determinants of coordination outcome

This table shows the determinants of the minimum action and the average action in the final round of the simulations as obtained from OLS regressions. In specifications with non-zero mistake probabilities, each minimum action and average action is averaged over 100 repetitions of the same configuration. Omitted categories are specifications with 2 agents, message costs of 1, zero communication and action stage mistake probabilities, uniform mistake distributions in the communication and action stages, and zero initial rounds with mandatory communication. Indicator variables for the number of available actions and an intercept term are included in all specifications but omitted to conserve space. Robust standard errors are shown in parentheses; statistical significance is indicated with *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Dependent variable	<i>Minimum Action in Final Period</i>	
$\lambda = 20/12$	0.093***	(0.010)
$\lambda = 20/11$	0.907***	(0.010)
$\lambda = 20/10$	1.190***	(0.011)
$\lambda = 20/9$	1.193***	(0.011)
Group of 4 agents	-0.690***	(0.011)
Group of 6 agents	-1.184***	(0.011)
Group of 8 agents	-1.570***	(0.011)
Group of 10 agents	-1.889***	(0.012)
Message costs of 3	-0.008	(0.010)
Message costs of 5	-0.002	(0.010)
Message costs of 7	-0.002	(0.010)
Message costs of 9	-0.045***	(0.010)
<u>Communication routines</u>		
First round with mandatory communication	0.397***	(0.008)
First two rounds with mandatory communication	0.572***	(0.008)
<u>Mistake/Experiment Probabilities</u>		
Action mistake probability of 10%	-1.521***	(0.008)
Action mistake probability of 20%	-1.977***	(0.009)
Communication mistake probability of 10%	0.302***	(0.008)
Communication mistake probability of 20%	0.555***	(0.008)
<u>Mistake/Experiment Distributions</u>		
Double-Distance-Half-as-Likely (action stage)	0.479***	(0.007)
Double-Distance-Half-as-Likely (comm. stage)	-0.148***	(0.010)
Exponential (comm. stage)	0.444***	(0.009)
Highest Message (comm. stage)	0.540***	(0.009)
Observations/Number of Simulations	135,000	
R-squared	0.769	

Table 3: Team size and routine effectiveness

This table analyzes the impact of team size on the effectiveness of communication routines and experiment parameters. It shows the coefficients of an OLS regression with dependent variable *Minimum action in the final period* of the simulations. The independent variables are the same as in Table 2, augmented by interaction terms for each team size (that is, 4, 6, 8, 10 agents) with each of the mistake probabilities, mistake distributions and communication routines. Column 1 shows the estimated coefficient on the first variable of the interaction term alone, while columns 2-5 show the estimated coefficients for the interaction terms. Robust standard errors are shown in parentheses; statistical significance is indicated with *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Dependent variable	Minimum action in final period				
	Coefficient on variable that is first part of the interaction term	Second part of interaction term			
	(1)	(2)	(3)	(4)	(5)
<u>Communication routines</u>					
First round with mandatory communication $\times \dots$	0.182*** (0.018)	0.221*** (0.024)	0.255*** (0.024)	0.316*** (0.024)	0.285*** (0.025)
First two rounds with mandatory communication $\times \dots$	0.351*** (0.018)	0.219*** (0.024)	0.266*** (0.024)	0.326*** (0.024)	0.292*** (0.025)
<u>Experiment/Mistake probabilities</u>					
Experiment in action stage (10%) $\times \dots$	-0.296*** (0.018)	-0.945*** (0.024)	-1.484*** (0.024)	-1.780*** (0.024)	-1.918*** (0.024)
Experiment in action stage (20%) $\times \dots$	-0.502*** (0.018)	-1.252*** (0.025)	-1.840*** (0.024)	-2.103*** (0.025)	-2.179*** (0.025)
Experiment in communication stage (10%) $\times \dots$	-0.004 (0.017)	0.602*** (0.024)	0.405*** (0.024)	0.287*** (0.024)	0.237*** (0.025)
Experiment in communication stage (20%) $\times \dots$	0.016 (0.018)	0.832*** (0.025)	0.754*** (0.024)	0.610*** (0.025)	0.499*** (0.026)
<u>Experiment/Mistake distributions</u>					
Comm. stage: Exponential distribution $\times \dots$	0.498*** (0.019)	-0.012 (0.026)	-0.026 (0.025)	-0.105*** (0.026)	-0.125*** (0.027)
Comm. stage: Highest Message distribution $\times \dots$	0.654*** (0.020)	-0.078*** (0.027)	-0.101*** (0.026)	-0.176*** (0.027)	-0.214*** (0.028)
Comm. stage: Double-Distance-Half-as-Likely distribution $\times \dots$	-0.055*** (0.020)	-0.257*** (0.027)	-0.140*** (0.027)	-0.069** (0.027)	0.004 (0.029)
Action stage: Double-Distance-Half-as-Likely distribution $\times \dots$	0.187*** (0.014)	0.391*** (0.019)	0.440*** (0.019)	0.372*** (0.019)	0.258*** (0.020)