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Communication and behavior in organizations: An experiment

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Abstract

Communication and behavior in organizations: An experiment*

We design a laboratory experiment to study behavior in a multidivisional organization facing a trade-off between coordinating its decisions across the divisions and meeting division-specific needs that are known only to the division managers. The managers communicate their private information through cheap talk. While the results show close to optimal communication, we also find systematic deviations from optimal behavior in how the communicated information is used. Specifically, subjects' decisions show worse than predicted adaptation to the needs of the divisions in decentralized organizations and worse than predicted coordination in centralized organizations. We show that the observed deviations disappear when uncertainty about the divisions' local needs is removed and discuss the possible underlying mechanisms.

JEL Classification: C70, D03, C92

Keywords: communication, coordination, decentralization, experiment

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1 Introduction

Coordination problems play a central role in organizations. Firms coordinate production decisions across divisions, districts in federal systems coordinate policies, and NGOs coordinate their decisions across countries. Often, such problems are complicated by privately known motives of the decision makers.[1] Two division managers attempting to coordinate their business strategies, for instance, might have incomplete knowledge of each other's goals. When this is the case, coordination can be facilitated by a communication channel between the managers, such as that established in General Motors by Alfred Sloan in the 1920s (Alonso et al., 2008).

While the manner in which private information is communicated and used to coordinate decisions has been explored in recent theoretical work,[2] key predictions of these models remain to be tested. The present paper uses a laboratory experiment to provide a first attempt, focusing on the question below:

Main Question. *What effect does the structure of an organization have on (i) how precisely private information is communicated and (ii) how the communicated information is used?*

Following Alonso et al. (2008), the experiment makes use of two types of organizational structures, centralized and decentralized, operationalizing them as simple coordination games.[3] A decentralized game is played between two agents, with a single decision to be made by each.[4] An agent has private information about her *local conditions*, which affect the payoff the agent receives from her own decision. She incurs an adaptation loss if her decision fails to adapt to her local conditions, and a coordination loss if her decision is not perfectly aligned with the decision of the other agent, therefore facing a trade-off between adaptation and coordination. The agents can communicate with each other before making their decisions.

[1] Several literatures build on this insight. Carlsson and Van Damme (1993) apply this idea in the context of global games; Baliga and Sjöström (2004) in the context of games of conflict; Dessein and Santos (2006) in the context of organizational economics.

[2] See, e.g., Alonso et al. (2008), Rantakari (2008), Dessein et al. (2010), Alonso et al. (2013).

[3] While intermediate cases in which the principal retains some, but not all, of the decision making authority can also be considered (Rantakari, 2008), the two extreme cases provide the sharpest contrast in theoretical predictions and are therefore particularly well-suited to implementation in the lab.

[4] In applications of the model, an agent could be a manager in charge of a division or a function within a firm, a local district, a state government, etc.

In a centralized game, decision rights are delegated to an unbiased coordinator, referred to as the *principal*, who maximizes joint profits and is uninformed about both local conditions. The agents can communicate their private information to the principal before the decisions are made. Because the answer to our Main Question above in theory depends on the size of incentives to coordinate, the experimental treatments independently manipulate the structure of the game (centralized vs. decentralized) and the importance of coordination (high vs. low) for individual payoffs.

We find that models in the organizational economics literature capture key features of how subjects communicated in the experiment, but provide an incomplete explanation of how the communicated information was used. Furthermore, the direction in which subjects' behavior deviated from the theory was closely tied to how authority was allocated within the game.

The importance of coordination was parametrized in the experiment as $\gamma \in [0, 1]$, with the interpretation that coordination is irrelevant when $\gamma = 0$ and adaptation is irrelevant when $\gamma = 1$. We find that the principal behaved *as if* the importance of coordination was smaller than it actually was, i.e., focused too much of her efforts on adapting to the agents' privately known states, while behavior of the agents under decentralization exhibited the opposite pattern. Thus, the agents focused too much of their efforts on coordination, behaving *as if* the importance of coordination was larger than it actually was in the experiment. We summarize these deviations from the theory as follows:

Main Result 1. *The importance of coordination was overweighted by the agents under decentralization and underweighted by the principal under centralization.*

Estimating the effect of the observed over- and underweighting on payoffs, we find that 94% of the difference between the optimal and the observed losses can be explained by the distortions in decision rules, with the remaining 6% due to communication. This is our second main result:

Main Result 2. *Most payoff losses were due to distortions of decision rules rather than miscommunication.*

Our starting point in explaining the observed distortions is that uncertainty enters the players' payoff functions differently under centralization and decentralization. Under decentralization, adaptation involves no uncertainty (since own states and decisions are known), while coordination involves the other agent's potentially uncertain decision. Under centralization, coordination involves no uncertainty (since both decisions are known), while adaptation involves the two agents' unknown states. Thus, one way to interpret Main Result 1 above is that the subjects overweighted the *uncertain* part of their payoff functions in all treatments.

To test the hypothesis that the observed deviations were driven by uncertainty, we use data from additional treatments with complete information and unique equilibrium predictions, but otherwise identical to their counterparts in the first stage of the experiment. Consistent with the hypothesis, we find no significant distortions in decision weights on average in these additional treatments:

MAIN RESULT 3. *With complete information, there was no over- or underweighting of the importance of coordination on average.*

Section 4 of the paper provides several possible channels for how uncertainty might have led to the observed deviations from equilibrium behavior. We show there that the data is consistent with ambiguous communication in the presence of ambiguity-averse message receivers as well as a simpler explanation based on gift-exchange. We also argue in Section 4 that the observed deviations from equilibrium behavior were unlikely to be caused by social preferences or risk aversion.

Our paper makes several methodological contributions to the experimental cheap talk literature. First, we elicit subjects' beliefs about their matched subjects' states and use the elicited beliefs to construct an empirical counterpart to the residual variance of communication, a measure commonly used in theoretical work.[5] This allows us to formulate predictions about *how well* subjects communicate without relying on assumptions about *how* they do it. Second, we use the elicited beliefs together with the equilibrium decision rules to study how subjects decide conditional on the communicated information. This allows us to test theoretical predictions about subjects' decision rules directly. Third, we use the elicited beliefs to perform a detailed payoff analysis that decomposes subjects' losses into a component due to miscommunication and a component due to deviations from equilibrium behavior.

The closest experimental study to ours is Brandts and Cooper (2015). While they also compare centralized and decentralized coordination games, they do not investigate the role of communication in coordinating multiple decisions. Moreover, the games they use are different from ours. Specifically, the agents are symmetrically informed about each others' local conditions as well as a *global* state of the world, which affects the payoffs of each

[5] We also perform robustness checks of our results that do not rely on belief elicitation.

player, while the principal is uninformed about the global state but informed about the agents' local conditions. Unlike Brandts and Cooper, we focus on communication of private information and its effect on coordination.[6]

Our paper also contributes to the experimental literature investigating strategic information transmission in the spirit of Crawford and Sobel (1982).[7] Most of this literature has focused on one sender-one receiver games, with more recent work investigating the case of multiple senders (Vespa and Wilson, 2016). While we also consider the case of multiple senders, our focus is on using communication to coordinate multiple decisions as opposed to information aggregation.

The implications of uncertainty in coordination problems have only recently begun to be studied in communication games with incomplete information.[8] We show experimentally that uncertainty biases subjects' decision rules in a manner that depends on how authority is allocated within an organization, and our results suggest a promising direction for future work.

2 Experimental Design

Our experimental design is based on the models of Alonso et al. (2008) and Rantakari (2008). Every treatment of the experiment has two players, 1 and 2, and two decisions, $d_1 \in D$ and $d_2 \in D$, to be made. The set D is a discretization of the interval $[-1, 1]$ in increments of 0.01; that is, $D = \{-1, -0.99, -0.98, ..., 0.98, 0.99, 1\}$.[9] The payoff of Player $i \in \{1, 2\}$ is given by

$$\pi_i = -(1-\gamma)(d_i - \theta_i)^2 - \gamma(d_i - d_j)^2, \quad i \neq j, \tag{2.1}$$

[6]Experimental economists have long been interested in coordination problems (see, e.g., Van Huyck et al., 1990; Brandts and Cooper, 2006). Some existing studies also explore the role of communication as a coordination device (see, e.g., Cooper et al., 1992; Blume and Ortmann, 2007).

[7]See, e.g., Dickhaut et al. (1995), Blume et al. (2001), Cai and Wang (2006), Sánchez-Pagés and Vorsatz (2007), and Wang et al. (2010).

[8]See Wilson and Vespa (2017), who find that strategic uncertainty in a repeated cheap talk game leads to a failure to coordinate on efficient equilibria. Behavior is consistent with a repeated babbling equilibrium even when Pareto-superior equilibria exist in which the sender uses a truthful strategy.

[9]The decision space is restricted because allowing the decisions to be elements of $\mathbb{R}$ would make it possible for a player who behaves randomly, or simply makes a mistake while typing, to sustain enormous losses, making the experiment infeasible. While $D = \mathbb{R}$ in Alonso et al. (2008) and Rantakari (2008), the restriction to $[-1, 1]$ does not affect the theoretical predictions. A discretization of $[-1, 1]$ is used because decisions in experiments can only approximate continuous variables.

where θ_i is Player i's state, or local conditions. The first component of the payoff function captures the *adaptation loss* arising from the mismatch between d_i and θ_i. The second component captures the *coordination loss* arising from the mismatch between the two decisions. As noted above, the parameter $\gamma \in [0, 1]$ measures the importance of coordination for the players. It is common knowledge that θ_1 and θ_2 are drawn independently from the set $\Theta = D$, with each state being equally likely.

The experiment has four initial treatments, **Decentralized-High**, **Centralized-High**, **Decentralized-Low**, **Centralized-Low**.[10] In the two **Decentralized** treatments, Player 1 makes decision d_1, Player 2 makes decision d_2, and each match consists of two players. In the two **Centralized** treatments, the decisions d_1 and d_2 are made by an additional Player 3 (the principal), whose payoff is given by the average of the payoffs of Player 1 and Player 2:[11]

$$\pi_3 = \frac{\pi_1 + \pi_2}{2}.$$

Each subject starts the session with an initial endowment and loses points in each period based on the decisions made in the period. In the **High** treatments, the points lost by Player 1 and Player 2 in each period of the game are determined by the following formula:

$$\pi_i = -(d_i - \theta_i)^2 - 3 \cdot (d_i - d_j)^2 \qquad i = 1, 2,\ i \neq j, \tag{2.2}$$

which corresponds to a choice of $\gamma = 3/4$.[12] Thus, the High treatments place a higher weight on coordinating d_1 and d_2 than on adapting to each state θ_i. The **Low** treatments place a high weight on adaptation to θ_i ($\gamma = 1/4$):

$$\pi_i = -3 \cdot (d_i - \theta_i)^2 - (d_i - d_j)^2 \qquad i = 1, 2,\ i \neq j. \tag{2.3}$$

The timing in the decentralized treatments is as follows. First, Player 1 and 2 privately observe their local conditions; that is, Player i observes θ_i, but not θ_j, $j \neq i$. Then, each player is asked to send a message $m \in M = \Theta$ to the other player. The framing of the screen is intentionally left neutral to avoid any suggestion on how to use the messages.[13] This is followed by an empty box and an OK button in the bottom right corner of the

[10] We also ran some additional treatments, which we describe later.

[11] For Player 3, the payoff is equal to the average to ensure that the losses do not substantially differ in magnitude from those of Player 1 and Player 2.

[12] The actual points lost are multiplied by a factor of 4 to make the payoff functions easier for subjects to understand.

[13] Specifically, the sender sees the following information displayed on her screen: "You are Player X. Your number *[local conditions]* is X. Send your message."

screen. After both messages are sent, they are simultaneously revealed to both players. Then, the players are asked to make their decisions. After the decisions are made, but before they are made public, the players make incentivized conjectures of each other's states: Player 1 guesses θ_2, and Player 2 guesses θ_1. At the end of each match, the players receive feedback.[14]

In the centralized treatments, Player 1 and Player 2 also start each match by privately observing their local conditions. Player 3 observes neither θ_1 nor θ_2. Then, Player 1 and 2 are each asked to send a message to Player 3. The screens that Player 1 and 2 see at this stage are identical to those displayed in the decentralized treatments. While the senders decides what messages to send, Player 3 waits. After both messages are sent, they are simultaneously revealed to Player 3, and this player is asked to make the two decisions. After the decisions are made, the messages are made public, and all players make conjectures about the states not known to them: Player 1 guesses θ_2, Player 2 guesses θ_1, and Player 3 guesses both θ_1 and θ_2. As in the decentralized treatments, these conjectures are incentivized. At the end of the match, all players receive feedback.[15]

In all of our treatments, the state, message, and decision spaces are restricted to be equal to each other. Thus, the θ_i, m_i, and d_i variables are all selected in increments of 0.01 from the set $\{-1, -0.99, -0.98, ..., 0.98, 0.99, 1\}$. Restricting the message space to be equal to the state space, as in Cai and Wang (2006), can be motivated from the observation that subjects tend to interpret messages in cheap talk games using a natural language (see, e.g., Blume et al., 2001).[16]

[14]The feedback information consists of the other player's state, the other player's decision, own points lost due to the decisions made, own points lost from the conjecture about the other player's state, points lost in the period, points lost so far, and pesos lost so far.

[15]The feedback information consists of the unknown state(s), Player 3's decisions, own points lost from the decisions made, own points lost from the conjecture(s) about the other state(s), points lost in the period, points lost so far, and pesos lost so far.

[16]While we thought about allowing for free communication in the experiment, we decided in favor of a more restricted communication protocol (i) because this allowed for a more direct test of the theory, (ii) because this approach was followed by other experimental studies in the strategic communication literature (e.g., Cai and Wang (2006)), and (iii) because we do not think that free communication would eliminate strategic uncertainty, multiplicity of equlibria, or the possibility of ambiguous communication. Even if communication were unrestricted, subjects could in principle use ambiguous messages such as "my state is close to zero" or "my state is 0.2 units away from zero," etc. In the experiment with free communication, the sender's interpretation of a message would still be conditional on beliefs about what communication rule is being used. Strategic uncertainty is not the result of our experimental design but rather an intrinsic feature of cheap talk games.

We use subjects' elicited beliefs to measure the quality of communication in the experiment (Section 3.1) and analyze how the communicated information is used in the decision-making stage (Section 3.2). Subjects' conjectures of each other's states are obtained with quadratic scoring rules (Nyarko and Schotter, 2002).[17] For Player 1 and Player 2, the points lost for the guesses are equal to the square of the distance between the conjecture and the true value of the state being guessed.[18] In the centralized treatments, Player 3 also guesses the states of both Player 1 and Player 2.[19] We interpret subjects' elicited conjectures as proxies of their posterior beliefs. While Section 4 of the paper discusses some of the issues associated with belief elicitation, we also note that our main results survive robustness checks that do not use subjects' elicited beliefs.

After analyzing the data from the initial treatments, we ran two additional treatments to test our explanations of the observed deviations from the theory. The treatments are identical to Centralized-High and Decentralized-High in all respects except that local conditions are common knowledge to all players. We provide more details in Section 4.

2.1 Implementation

The experiment was conducted at Instituto Tecnológico Autónomo de México in Mexico City between October 2014 and September 2015 using the software z-Tree (Fischbacher, 2007). After entering the laboratory, sitting down at their computer terminals, and signing the consent forms, the subjects are distributed their treatment's instructions.[20] At the same time that the subjects are reading the instructions, a quiz is displayed on their computer screens. The subjects are informed that they have 20 minutes to read the instructions and complete the quiz.[21]

[17] Quadratic scoring rules incentivize risk-neutral subjects to report their mean beliefs truthfully.

[18] Formally, denote Player i's conjecture about θ_j, conditional on having received message m_j, by $p(\theta_j|m_j)$. The points lost for the conjecture are given by $(p(\theta_j|m_j) - \theta_j)^2$.

[19] For this player, the points lost are equal to the average of the two squared distances to ensure that the losses for the guesses do not strongly differ from those of Player 1 and Player 2.

[20] See the online appendix at http://piotr-evdokimov.com/Appendix-Instructions.pdf. While the sample instructions are in English, the actual instructions were administered in Spanish.

[21] The quiz has 8 questions that are identical for all treatments, and 4 that differ across the decentralized and centralized treatments. The quiz tests the subjects' understanding of statistical independence, how they are to be matched in the experiment, the conversion of points to pesos, and the game's basic structure. The answers to all of the quiz questions are incentivized: each subject gains one Mexican peso for each quiz question correctly answered. The questions are included in the online appendix.

The treatments are implemented between subjects. Each session of the experiment consists of two practice periods followed by fifteen periods that count towards each subject's earnings. In each period, subjects are randomly and anonymously matched with randomly-assigned roles at the beginning of each period.

The subjects' earnings are determined as follows. Every subject is guaranteed a 30 Mexican pesos ($\approx$ US\$2) show up fee in addition to the earnings from the quiz. These earnings are called the subject's "guaranteed earnings." In addition, each subject is given 210 Mexican pesos ($\approx$ US\$15). In each (non-practice) period of the game, each subject loses a number of points due to her decisions and the decisions made by the subjects with whom she is matched during the period. In addition to losing points from the game, the subjects lose points from their conjectures of other players' states in accordance to the quadratic scoring rule described above. The subject's "additional earnings" are determined as follows:

$$\textit{Additional earnings} = 210 - 3 \times \textit{Total points lost during the experiment.}$$

Each subject's total earnings are given by the sum of the guaranteed and additional earnings.[22] It is explained to the subjects that any subject losing more than 50 cumulative points (150 Mexican pesos) would be excluded from further matches, and that in the event this happens, the remaining subjects will be rematched with each other, with some randomly chosen subjects sitting out in each subsequent match. In practice, this never happened, but the program we used allowed for the contingency.

2.2 Predictions

The communication rule of sender i is a mapping $\mu_i : \Theta \to \Delta M_i$ from local conditions to probability distributions over messages. Under decentralization, the decision rule of receiver i is a mapping $d_i^D : \Theta \times M_1 \times M_2 \to \mathbb{R}$, $i \in \{1,2\}$, from local conditions and messages to decisions. Under centralization, the decision rule of the sole receiver (Player 3) is a pair of mappings $d_i^C : M_1 \times M_2 \to \mathbb{R}$, $i \in \{1,2\}$, where d_i^C maps a pair of messages (m_1, m_2) to a decision for Player i. The belief functions of receiver i are the mappings $\eta_j : M_j \to \Delta\Theta$, $j \in \{1,2\}$, each denoting the probability assigned by the receiver to each state $\theta_j \in \Theta$ after receiving message m_j from sender j.

[22]The instructions provide subjects with several examples of final earnings as a function of points lost, and the quiz tests their understanding of the payment rules with yet another example.

A communication equilibrium is defined by communication rules for Player 1 and Player 2 ($\mu_1(m_1|\theta_1)$ and $\mu_2(m_2|\theta_2)$), decision rules for the decision makers ($d_i^D(m_1, m_2, \theta_i)$ under decentralization, and $d_i^C(m_1, m_2)$ under centralization), and belief functions for the receivers ($\eta_1(\theta_1|m_1)$ and $\eta_2(\theta_2|m_2)$) such that the communication rules are optimal given the decision rules, the decision rules are optimal given beliefs, and the beliefs are derived from the communication rules using Bayes' rule whenever possible.

We define $E[\theta_i|m_i]$, $i = 1, 2$, as the posterior belief held by the receiver of message m_i about local conditions θ_i. Following the theoretical literature, we measure the quality of communication through the residual variance of the posterior belief, defined as $E\left[(\theta_i - E[\theta_i|m_i])^2\right]$. Higher residual variance means more dispersion in the posterior beliefs and thus lower quality of communication. The advantage of such a measure in experimental settings is that the residual variance of communication is defined independently of the partitional structure of equilibrium.[23] Therefore, it can be used to measure communication quality whether or not players are conforming to any particular equilibrium or even exhibiting non-equilibrium behavior.

It is well-known that communication games admit a multiplicity of equilibria.[24] We therefore formulate most of our predictions about equilibrium communication around the Most Informative Equilibrium (MIE). We base our predictions on MIE for several reasons: *i*) it is the equilibrium selection rule used in the theoretical literature;[25] *ii*) MIE maximizes ex-ante expected payoffs and it is therefore the right benchmark to compare payoff losses in the experiment; *iii*) it leads to clear theoretical predictions. A different equilibrium selection rule might generate potentially different predictions given the large number of possible equilibrium choices across our treatments. Ultimately, we address the question of what, if any, equilibrium is played using the experimental data.

Theory predicts the following about communication in MIE:

Prediction 1 (Communication).

1. *The residual variance of communication is lower under centralization than decentralization, for any* $\gamma \in (0, 1)$.

[23] Alonso et al. (2008) and Rantakari (2008) show that any equilibrium in which a finite number of messages is possible is economically equivalent to one in which the communication rules take a partitional form: a sender partitions the state space and only communicates which element of the partition the realized state belongs to.

[24] It is also well-known that an uninformative equilibrium always exists in such games.

[25] Chen et al. (2008) provide conditions which uniquely select MIE in cheap talk games.

2. *As the importance of coordination increases, the residual variance of communication increases under centralization while it decreases under decentralization.*

The logic behind Prediction 1 is the following. Since the agents maximize their own individual payoffs, while the principal cares about the payoffs of both agents, the incentives of the agents are more aligned with the incentives of the principal than they are with each other. This leads communication to be more informative under centralization than decentralization, as long as $\gamma < 1$. As γ increases under centralization, the principal cares less about adapting to local conditions and information becomes less relevant, distorting incentives of senders toward exaggeration. As γ increases under decentralization, the increased consequences of coordination failure provide incentives for better communication.[26]

Recall that $E[\theta_i|m_i]$ denotes the posterior expectation about i's state held by the receiver of the message following message m_i. Under decentralization, Player i makes the following decision in equilibrium after receiving the message m_j:

$$d_i^D = (1-\gamma)\theta_i + \frac{\gamma^2}{1+\gamma}E[\theta_i|m_i] + \frac{\gamma}{1+\gamma}E[\theta_j|m_j], \quad i = 1, 2, \quad i \neq j. \tag{2.4}$$

The agent's decision rule is a linear function of her own state θ_i, her own posterior $E[\theta_j|m_j]$, and the other agent's posterior $E[\theta_i|m_i]$. When the importance of coordination is low, both agents put large weights on their own local conditions and small weights on the other pieces of information. As coordination needs increase, both players increase the weight on the information provided by the other player, and decrease the weight on their own private information, which leads to more coordination in equilibrium.[27] We estimate the decision rule in Equation 2.4 as part of our statistical analysis of the data to quantify the magnitude and direction of the deviations from optimal behavior.

Under centralization, the principal makes the following decisions after receiving the

[26] Prediction 1 is robust to social preferences. Alonso et al. (2008) consider a variation of the model described above in which Player 1 maximizes $\lambda\pi_1 + (1-\lambda)\pi_2$ and Player 2 maximizes $(1-\lambda)\pi_1 + \lambda\pi_2$, where $\lambda \in \left[\frac{1}{2}, 1\right]$. Although the payoff functions used in the experiment set $\lambda = 1$, it is in principle plausible that Player 1 and Player 2 assign strictly positive weights to each other's payoffs. However, for a fixed γ, it can be shown that the difference in the quality of communication under centralization and decentralization, while shrinking as λ approaches $\frac{1}{2}$, remains strictly positive. Similarly, for any fixed λ, the arguments regarding the effect of γ on the quality of communication remain valid.

[27] It can be shown that the decisions converge to each other as $\gamma \to 1$.

message $m = (m_1, m_2)$:[28]

$$d_i^C = \frac{1+\gamma}{1+3\gamma} E[\theta_i | m_i] + \frac{2\gamma}{1+3\gamma} E[\theta_j | m_j], \quad i = 1, 2, \quad i \neq j. \tag{2.5}$$

The decision rules are functions of the principal's posterior beliefs about the players' states. When the importance of coordination is low, the posterior about Player i's state has a much larger weight in determining d_i than the posterior about the state of Player j. As the importance of coordination increases, the weights on the two posteriors become closer to each other. These comparative statics can be summarized as follows:

PREDICTION 2 (OPTIMAL DECISIONS). *As the importance of coordination increases:*

1. *Under centralization, Player 3 puts more weight on the information communicated by Player j when making decision d_i.*

2. *Under decentralization, Player i, $i = 1, 2$, puts less weight on her own local conditions and a larger weight on the information communicated by Player j.*

We can also use the decision rules in Equation 2.4 and Equation 2.5 to formulate predictions about average degrees of adaptation and coordination in the experiment. The advantage of centralization lies in the principal's ability to perfectly control the degree to which the decisions are coordinated with each other. The principal, however, lacks complete knowledge of the other players' local conditions, which makes adaptation difficult. By contrast, under decentralization, the players can perfectly control the degree of adaptation of their decisions to their own local conditions, but coordination is difficult because each player only controls her own decision.

Let $CL_k = E[(d_1 - d_2)^2]$, $k \in \{C(entralized), D(ecentralized)\}$, denote the expected (normalized) coordination loss.[29] In MIE, the principal's comparative advantage at coordination generates a smaller coordination loss under centralization than under decentralization. Moreover, as γ increases, the coordination loss falls regardless of how authority is allocated.[30] This implies the following prediction, which is proved in Proposition 1 of the online appendix:

[28]See Alonso et al. (2008) and Rantakari (2008) for derivations of the decision rules described in this section.

[29]This quantity is normalized by γ and hence does not represent actual utility or point losses.

[30]The model is sufficiently tractable to also allow the computation of correlations between decisions, and between decisions and states, in closed form. However, we base our predictions on coordination and adaptation losses (see below) because they are easier to test compared to predictions based on correlation coefficients.

Prediction 3 (Coordination Losses).

1. *The average coordination loss is larger under decentralization than centralization.*
2. *As the importance of coordination increases, the average coordination loss decreases under both centralization and decentralization.*

Similarly, we can compute the expected (normalized) adaptation loss in MIE for an arbitrary Player i, $i = 1, 2$, denoted by $AL_k^i = E[(d_i^k - \theta_i^k)^2]$, $k \in \{C, D\}$. The agents' comparative advantage at adaptation leads to larger adaptation losses under centralization than under decentralization. As coordination becomes more important, the adaptation loss rises regardless of how authority is allocated.[31] The following prediction is proved in Proposition 2 of the online appendix:

Prediction 4 (Adaptation Losses).

1. *The average adaptation loss is larger under centralization than decentralization.*
2. *As the importance of coordination increases, the average adaptation loss increases under both centralization and decentralization.*

Thus, the games lend themselves to a rich array of predictions about communication quality, decision rules, and adaptation/coordination losses. We now describe the experimental data.

3 Results

For the initial treatments with incomplete information, we collected data from 238 undergraduate students recruited from introductory level classes.[32] A total of 14 experimental sessions were conducted with a minimum of 11 students and a maximum of 21 students per session. The distribution of subjects among treatments is shown in Table 1.[33] More sub-

[31]This has no immediate implication for welfare because an increase in γ also implies that adaptation losses have a lower impact on welfare.

[32]We also ran some additional treatments, described below in Section 4.

[33]The number of participants in the Centralized-High treatment is not divisible by three. This is because one of the subjects experienced a health issue while the instructions were being administered and had to leave the room. We re-calibrated the program in this session to accommodate 11 subjects rather than 12.

jects participated in the centralized treatments to ensure that the amount of observations (e.g., for d_1 and d_2) is not too unbalanced. A session lasted 75 minutes on average.

	Low γ	High γ
Decentralized	3 sessions $N = 48$	3 sessions $N = 56$
Centralized	4 sessions $N = 66$	4 sessions $N = 68$

Table 1: Subjects per treatment (initial treatments with incomplete information).

In what follows, we first discuss how subjects communicated in the experiment (Section 3.1), and second how the communicated information was used (Section 3.2). Section 3.3 quantifies the payoff consequences of deviations from equilibrium behavior, as well as the payoff consequences of miscommunication. All of our results focus on non-practice periods of the experiment.

3.1 How Private Information Was Communicated

The quality of communication is in theory measured in terms of the residual variance of the receiver's posterior, $E[\theta|m]$, around the sender's privately known state, that is, $E\left[(\theta - E(\theta|m))^2\right]$. To obtain a unit-free measure, we divide this variable by 1/3 (the residual variance in the babbling equilibrium). We then assess treatment effects on the empirical analogue of this object, by defining $3 \times (Other\_State_{it} - Guess_{it})^2$ as three times the squared distance between receiver i's guess in period t and the true value of the state.[34] If the mean of this variable is equal to 0.5, for instance, the interpretation is that one half of the no communication variance of beliefs around the true value of the state is observed in the data.

We regress $3 \times (Other\_State_{it} - Guess_{it})^2$ against treatment dummies, allowing the error

This was accomplished by matching 9 people in every period of the game, with two remaining participants sitting out randomly. We also informed the participants in this session about the new rematching procedure. Our results do not significantly change if this session is excluded from the analysis.

[34] We use all elicited guesses (in non-practice periods) of all subjects in our analysis of the quality of communication. In centralized treatments, the correlation between the guesses of Player 3 and those of Player 1 and Player 2 has a coefficient of $\rho = 0.855$.

term in the regression to be correlated for observations coming from the same session.[35] While the number of sessions is small, we assume within-session correlations because this assumption can be applied in the vast majority of our econometric analysis,[36] and, when possible, provide robustness checks with subject-clustered standard errors in the appendix.

	Decentralized		Centralized
$\hat{\gamma}$ when $\gamma = 0.25$	0.4272	$>^{**}$	0.1796
	(0.0574)		(0.0803)
	$\vee^{**}$		$\not\curlyvee$
$\hat{\gamma}$ when $\gamma = 0.75$	0.2164	$\not<$	0.3971
	(0.0789)		(0.2102)

Session-clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 2: Treatment effects on residual variance of communication. The $>^{**}$ and $\vee^{**}$ symbols denote differences that are significant at a 5% level. The $\not\curlyvee$ and $\not<$ symbols denote differences that are not statistically significant ($P > 0.1$).

The results are shown in Table 2. Consistent with Prediction 1, we find that the residual variance of communication was lower under centralization than decentralization when the importance of coordination was low ($P < 0.05$). The residual variance decreased with the importance of coordination under decentralization ($P < 0.05$), also as predicted. There was no significant difference between the residual variance under centralization and decentralization when γ was high ($P = 0.435$), which is also in line with Prediction 1, according to which the quality of communication converges to the same level in both organizational structures as γ increases. Inconsistent with Prediction 1, we find no significant effect of γ on the residual variance under centralization ($P = 0.351$).

Appendix A.3 provides some robustness checks of the result that the residual variance of communication was significantly higher under decentralization if and only if the importance of coordination was low. As shown there, the result is observed in later periods of the experiment taken separately, suggesting that the underlying effects were not learned away. It is also observed if residual variance is measured using subjects' messages as proxies for guesses. I.e., even if the analysis does not use subjects' elicited beliefs, which in

[35] Notice that subjects in the role of Player 3 made two guesses in every period.

[36] E.g., even under the assumption that residuals are independent across subjects, clustering by subject or using subject-level random effects is not appropriate when the unit of observation is a game, as in Section 3.2 below.

principle may be biased,[37] to form a measure of communication quality, we see some of the theoretically predicted comparative statics in the data. Moreover, the result is reflected in distributions at the level of individual subjects and not just within-treatment averages.

These results suggest that MIE was at least partially predictive of the treatment effects observed in the communication data. Directly comparing the predicted and observed residual variances of communication using the standard errors in Table 2, we find that the residual variances were not significantly lower than predicted in *any* of the treatments, and significantly higher than predicted in Decentralized-Low ($P < 0.01$). While this suggests at least some under-communication relative to MIE, it is consistent with behavior in other, less informative, equilibria. On the other hand, the way in which the communicated information was used deviated from the predictions of *any* communication equilibrium, not just MIE. These deviations, which are demonstrated in Section 3.2 below, are the mainstay of our paper.

3.2 How the Communicated Information Was Used

While our predictions about the optimal use of information are centered on subjects' decision rules (Equation 2.4 and Equation 2.5), it is instructive to first study the observed adaptation and coordination losses. This allows us to assess treatment effects without resorting to involved econometric analysis and to see if systematic deviations from optimal coordination and adaptation are present in the data. After noting and describing these deviations, we turn to a more rigorous analysis of subjects' decision rules.

Subjects' adaptation and coordination losses are plotted in Figure 1.[38] It can be seen from Figure 1 that, as predicted, subjects coordinated more and adapted less as coordination became more important, and that this was true both under centralization and decentralization. Specifically, as γ increased, the coordination loss decreased under centralization ($P < 0.001$), while the adaptation loss increased under both centralization ($P < 0.01$) and decentralization ($P < 0.05$). While the decrease in the coordination loss under decentralization was not statistically significant ($P = 0.1007$), the effect was in the right direction. That adaptation losses increased but coordination losses were little affected

[37] One possibly source of bias is risk aversion. The results in this section are difficult to interpret if risk aversion on the part of the message receivers is assumed, as the direction of the bias would depend on assumptions about the message receivers' beliefs.

[38] We compute the standard errors by regressing $(d_i - \theta_i)^2$ and $(d_1 - d_2)^2$ against treatment dummies, with standard errors clustered by session. The regression results can be found in Table 22 in the appendix.

suggests a possible coordination failure in the Decentralized-High treatment.[39]

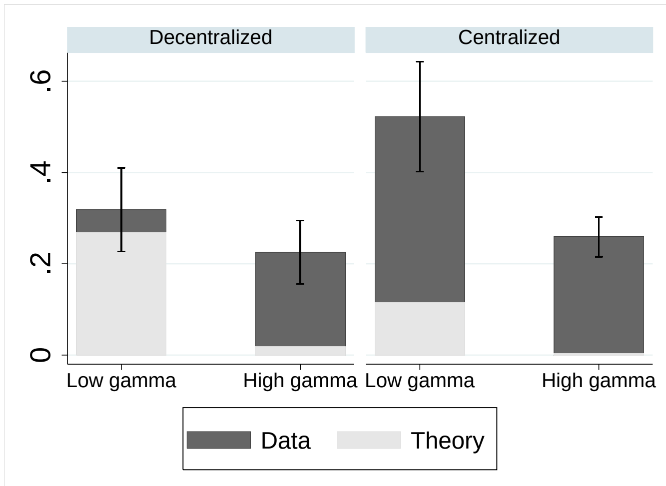
Because MIE maximizes agents' ex-ante expected payoffs, it provides a useful benchmark for how well subjects should adapt and coordinate. The treatment comparisons show that, with low γ, the coordination loss was higher under centralization than decentralization ($P < 0.05$), while the adaptation loss was higher under decentralization than centralization ($P < 0.01$). Both of these observations directly contradict Prediction 3 and Prediction 4, as well as the intuition that centralized organizations are better at coordinating while decentralized ones are better at adapting. When γ is high, the coordination loss was statistically indistinguishable under centralization and decentralization, as was the adaptation loss (both $P > 0.1$). These observations are also at odds with Prediction 3 and Prediction 4. Comparing the data to the MIE predictions directly, the coordination loss $(d_1 - d_2)^2$ was significantly greater than predicted for both values of γ under centralization ($P < 0.001$ in both cases), while the adaptation loss $(d_i - \theta_i)^2$ was significantly greater than predicted for both values of γ under decentralization ($P < 0.001$ in both cases). Taken together, the results in this paragraph suggest that decision makers under-adapted in decentralized treatments and under-coordinated in centralized ones.

To directly estimate the equilibrium decision rule under decentralization (Equation 2.4), we regress the decision made by subject i in period t ($Decision_{it}$) against subject i's state (θ_{it}), the guess of subject i's partner about subject i's state ($Guess\_of\_the\_State_{it}$), and the guess of subject i about her partner's state ($Guess\_of\_the\_Other\_State_{it}$).[40] To accommodate the effect of γ on subjects' decisions, we interact the explanatory variables with a dummy that takes on the value of one for treatments with $\gamma = \frac{3}{4}$. We also place the restriction that the weights add up to one both when $\gamma = \frac{1}{4}$ and when $\gamma = \frac{3}{4}$.[41] The results are shown in the first column of Table 3. As can be seen from the interaction terms, subjects qualitatively responded to incentives to coordinate and adapt roughly as theory predicts.

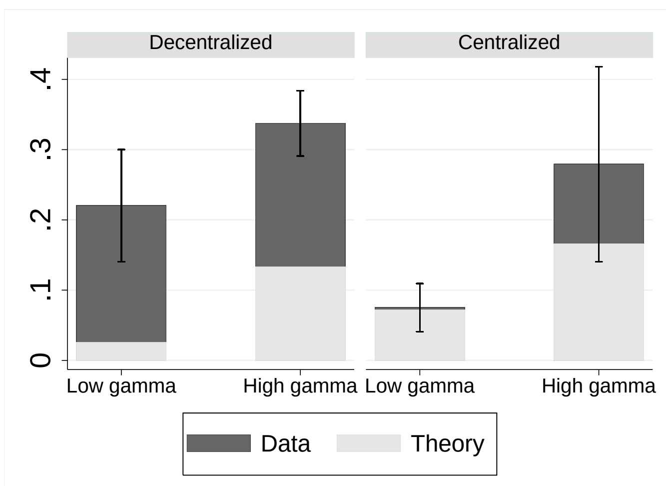
[39] Relative to MIE, we also find that the coordination loss was significantly higher than predicted in this treatment.

[40] Formally, the decision d_i made by Player i depends on her state θ_i, her belief about j' state, $E[\theta_j|m_j]$, and her second order belief about the belief held by Player j about state θ_i after having received message m_i, $E[\theta_i|m_i]$. We proxy this second order belief with the belief reported by Player j. While this second order belief equals $E[\theta_i|m_i]$ in any equilibrium, the two quantities might differ in the presence of deviations from equilibrium. To alleviate this concern, we perform a robustness check in the appendix by re-doing our analysis with received messages in place of reported beliefs and find similar results. Unlike elicited beliefs, messages are common knowledge even in the presence of equilibrium deviations.

[41] The results are qualitatively similar if this restriction is removed. As in the rest of our analysis, we allow the error terms ϵ_{it} to be correlated within a session. Robustness checks using subject-clustered standard errors can be found in the appendix.



$(d_1 - d_2)^2$



$(d_i - \theta_i)^2$

Figure 1: Observed misadaptation and miscoordination (dark grey) and MIE predictions (light grey).

As the importance of coordination increased, the weight on θ_{it} decreased ($P < 0.05$), and the weight on $Guess\_of\_the\_Other\_State_{it}$ increased ($P < 0.001$). Subjects' decisions put a smaller weight on the state and a larger weight on posterior beliefs when the incentive to coordinate was greater.

	Decentralized	Centralized
High (dummy=1 if $\gamma = \frac{3}{4}$)	-0.00735	0.0149
	(0.0131)	(0.0149)
State (θ)	0.493****	
	(0.0775)	
Guess of the State	0.162****	0.946****
	(0.0224)	(0.0196)
Guess of the Other State	0.345****	0.0544***
	(0.0572)	(0.0196)
$\theta \times$ High	-0.270**	
	(0.115)	
Guess of the State $\times$ High	0.0576	-0.290****
	(0.0939)	(0.0323)
Guess of the Other State $\times$ High	0.213****	0.290****
	(0.0598)	(0.0323)
Constant	0.0197	0.00615
	(0.0123)	(0.0118)
Observations	1560	1320

Session-clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 3: Estimated decision weights.

We use Equation 2.5 as a guide to estimate an analogous model for the centralized treatments. I.e., we regress the principals' decisions against their elicited posterior beliefs with the restriction that the weights sum up to one.[42] The results, reported in the second column of Table 3, suggest that the principals' decision rules responded in the predicted direction to changes in incentives to coordinate. Thus, the weight on $Guess\_of\_the\_State$

[42]To conserve the same variable names, we define $Decision_{jit}$ to be the decision made by principal j in period t on subject i's behalf, $Guess\_of\_the\_State_{jit}$ the principal's guess about subject i's state in period t, and $Guess\_of\_the\_Other\_State_{jit}$ the principal's guess about the other subject's state in period t.

decreased and the weight on *Guess_of_the_Other_State* increased when the importance of coordination was high ($P < 0.001$ in both cases). I.e., as coordination became more important, the principal weighted the belief about i's state less and the belief about the state of i's partner more when making a decision on behalf of subject i.

Importantly, while the responses to changes in incentives to coordinate were in the right direction both under centralization and decentralization, subjects' decisions showed significant and systematic quantitative deviations from equilibrium (Table 4). In Decentralized-Low, subjects underweighted their own states ($P < 0.001$), overweighted their partners' posteriors ($P < 0.001$), and overweighted their own posteriors about their partners' states ($P < 0.05$). In Decentralized-High, subjects overweighted their own posteriors ($P < 0.001$). Thus, subjects in the decentralized treatments underweighted their own states and overweighted their own and their partners' beliefs. In both Centralized-Low and Centralized-High, the principal put too much weight on the belief about θ_i and too little weight on the belief about θ_j when making decision d_i ($P < 0.001$ in both cases). These deviations are consistent with the hypothesis that decision makers overweighted the importance of coordination under decentralization and underweighted it under centralization.

Decentralized Treatments	θ_i	ν_i	ν_j
Low (Predicted)	0.75	0.05	0.2
Low (Actual)	0.49****	0.16****	0.34**
High (Predicted)	0.25	0.32	0.43
High (Actual)	0.22	0.22	0.56****

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Centralized Treatments	ν_i	ν_j
Low (Predicted)	0.71	0.29
Low (Actual)	0.95****	0.05****
High (Predicted)	0.54	0.46
High (Actual)	0.66****	0.34****

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 4: Predicted equilibrium weights and the actual weights in subjects' decision rules. The significance levels refer to the difference between actual and predicted weights.

To quantify the degree to which coordination was over- or underweighted, we structurally estimate the γ implied by the subjects' decisions under the null hypothesis of equilibrium. We do this separately for each of the experimental treatments using non-linear least squares and session-clustered errors.[43] The estimation results are shown in Table 5. The estimated γ's are significantly higher than what they should be (i.e., those specified in the instructions) in both Decentralized-Low and Decentralized-High ($P < 0.05$ and $P < 0.01$, respectively). For example, when $\gamma = \frac{3}{4}$, the agents acted as if adaptation is almost irrelevant. In Centralized-Low and Centralized-High, the weights are significantly lower than what they should be ($P < 0.001$ in both treatments). For example, when $\gamma = \frac{1}{4}$, the principal acted as if the weight on coordination were almost zero. We summarize these findings as follows:

	Decentralized	Centralized
$\hat{\gamma}$ when $\gamma = 0.25$	$0.517 >^{**} 0.25$	$0.0296 <^{****} 0.25$
	(0.103)	(0.0116)
$\hat{\gamma}$ when $\gamma = 0.75$	$0.9396 >^{***} 0.75$	$0.356 <^{****} 0.75$
	(0.0375)	(0.0548)
Observations	1560	1320

Session-clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 5: The estimated distortions of γ.

Main Result 1. *The importance of coordination was overweighted by the agents under decentralization and underweighted by the principal under centralization.*

To see how robust the result above is to learning, we modify the non-linear least squares model used in Table 5 by allowing the estimated $\hat{\gamma}$'s to differ across periods in every treatment of the experiment.[44] This reveals a significant time trend in the Decentralized-Low treatment, where the estimated $\hat{\gamma}$ loses significance by period 15 ($P = 0.345$). On the other hand, the overweighting in this treatment is still positive in period 15, and the lack of significance might simply be a question of power. We find no significant time effects on $\hat{\gamma}$ in Decentralized-High ($P = 0.496$), Centralized-Low ($P = 0.273$), or Centralized-High ($P = 0.266$). Taken together, these results suggest that the distortions identified in Table 5 are not easily learned away.

[43]We provide a number of robustness checks below, including ones in which coefficients are estimated at the level of individual subjects.

[44]The econometric details and estimation results are described in Appendix A.4.

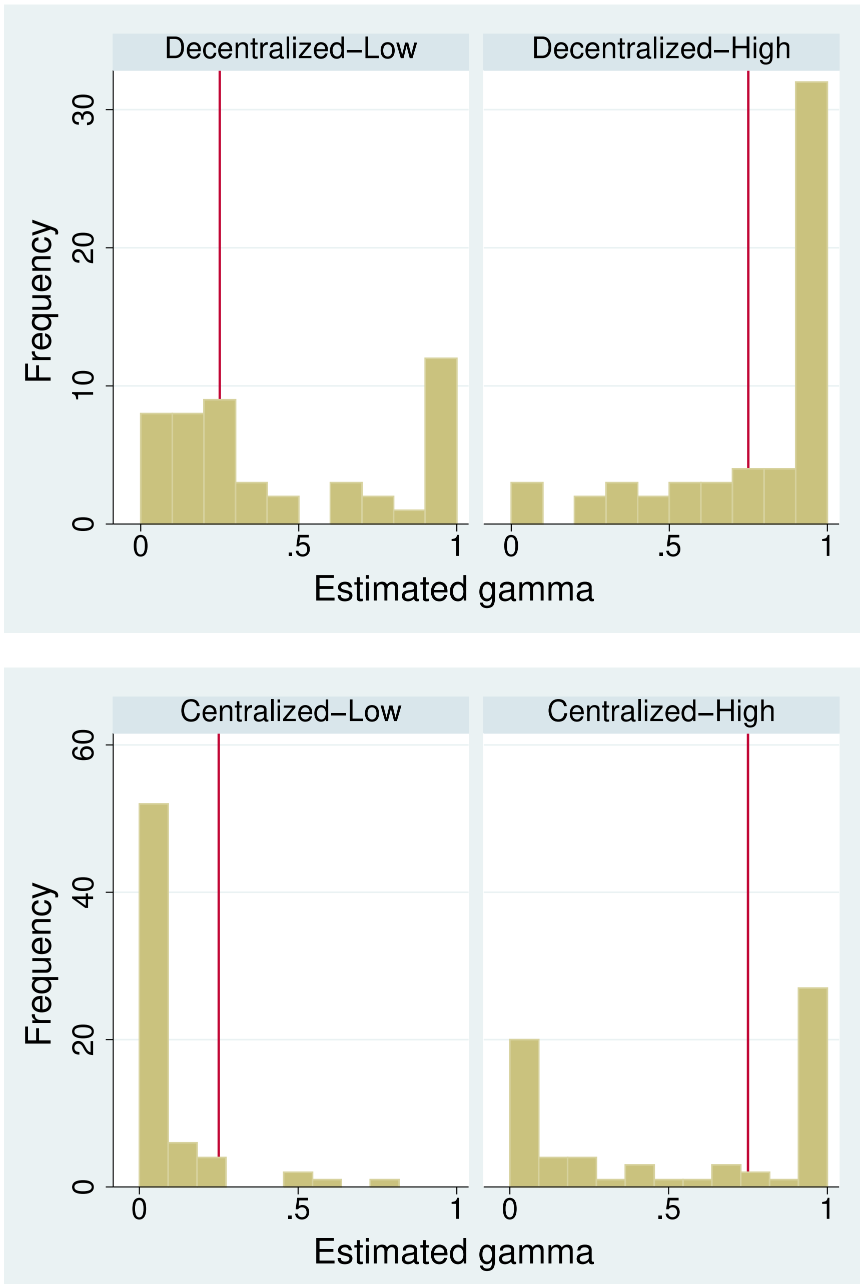


Figure 2: Heterogeneity in decision weights.

To study between-subject heterogeneity in deviations from equilibrium, we estimate subject-level regressions analogous to those in Table 5.[45] The subject-level estimates of γ in the four treatments are reported in Figure 2. The red vertical lines represent the predicted γ's of 0.25 and 0.75. As seen in the figure, a large fraction of subjects in the Decentralized-High treatment acted as if γ was close to one, while a large fraction of subjects in the Centralized-Low treatment acted as if γ was close to zero. It can also be seen that many subjects used a γ above 0.25 in the Decentralized-Low treatment and a γ below 0.75 in Centralized-High. While we omit a description of the relevant statistical comparisons here, it is argued in Appendix A.4.1, which compares the observed medians and means to their predicted values, that Main Result 1 is reflected not only in overall averages but also in distributions at the level of individual subjects.

While the analysis so far has made use of subjects' elicited beliefs, there is another way to identify deviations from equilibrium decision rules in our experiment. Specifically, the experimental design allows us to derive subjects' *implicit* beliefs under the assumption of equilibrium behavior. For the centralized treatments, given that we do observe the principal's decisions, the equilibrium decision rules in Equation 2.5 form a system of two equations in two unknowns which can be used to solve for $E(\theta_1|m_1)$ and $E(\theta_2|m_2)$. For the decentralized treatments, a similar procedure can be employed given knowledge of the decisions made by each player, the true states, and the equilibrium decision rules given by Equation 2.4. When we do this, we find that 43.19% of implicit beliefs lie outside the interval $[-1, 1]$ overall, with 50.96% under decentralization and 34.02% under centralization. This provides corroborative evidence of suboptimal behavior in both treatments.

Appendix A.4 provides additional robustness checks of Main Result 1. Specifically, Table 18 re-estimates the weights in Table 5 using subjects' messages in place of elicited beliefs; Table 19 re-estimates the weights in the centralized treatments replacing the beliefs of Player 3 with those of Player 1 and 2; Table 20 re-estimates the weights with standard errors clustered at the level of the decision maker; Appendix A.4.1 carries out the above-described analysis of heterogeneity in decision rules. We find qualitatively similar distortions of decision weights in every case.

[45] The model produces no estimate for one of the subjects in Centralized-High because this subject set each of the decisions to zero. As adaptation was ignored and full coordination achieved, we manually set $\hat{\gamma} = 1$ for this subject.

3.3 Payoff Consequences of Deviations From Equilibrium

We now turn to an analysis of subjects' losses in the experiment. On average, subjects earned 163.5 Mexican pesos ($\approx$ US\$11), excluding the show-up fee and the payment from the quiz.[46] Of the 46.5 pesos subjects lost on average from playing the game *and* making guesses about their partners' states, 91% were lost from the game and 9% from the guesses. While the average losses from playing the game were moderate, several subjects came close to bankruptcy (losing more than 150 pesos by period 15) in the course of the experiment, and there was significant variation across subjects, as shown in Figure 5 of Appendix A.5. Because only good decisions ensured subjects from incurring substantial losses, we believe that our experiment provided subjects with effective incentives.

For each team in our data set, we define the total *relative* payoff loss as the loss observed in the data minus the loss predicted by MIE:

$$L^{total} = L^{observed} - L^{MIE}.$$

To compute L^{MIE}, for every treatment, we calculate an explicit solution for the most informative partitional equilibrium provided by Alonso et al. (2008, pp. 171-172). We then derive the posterior beliefs that receivers would form in MIE.[47] Using these posterior beliefs, we compute the optimal decisions (using 2.4 and 2.5). Then, using 2.1, we compute the decision makers' utilities given the decisions. The payoffs of Player 1 and Player 2 are then added to calculate L^{MIE}.

We can further decompose the relative payoff loss as follows:

$$L^{total} = \underbrace{(L^{observed} - L^{reported\,beliefs})}_{\text{Loss due to distortions}} + \underbrace{(L^{reported\,beliefs} - L^{MIE})}_{\text{Loss due to miscommunication}}. \tag{3.1}$$

$L^{reported\,beliefs}$ is the team's payoff loss given the decision makers' reported beliefs. To compute it, we calculate the equilibrium predictions for d_i^C and d_i^D conditional on subjects' elicited beliefs. We then use Equation 2.1 to calculate individual utilities and add the utilities to calculate $L^{reported\,beliefs}$. This gives the total amount of points that each team would have lost if the decision makers followed the equilibrium decision rules using their reported beliefs. $L^{observed} - L^{reported\,beliefs}$ is labeled as the loss due to distortions in Equation

[46] At the time of the experiment, the minimum wage in Mexico was about 70 pesos per day, which is arguably a poor reference point for students at a private research university such as ITAM. For a better one, consider that the cost of a 15km Uber ride was around 80 pesos.

[47] Our simulation approximates the most informative equilibria by partitional equilibria with 231 elements.

3.1. We interpret this variable as the loss in payoffs due to subjects' decisions deviating from the equilibrium decision rules in Equation 2.4 and Equation 2.5. $L^{reported\,beliefs} - L^{MIE}$ is labeled as the loss due to miscommunication. This variable captures the payoff loss due to subjects' posterior beliefs deviating from those suggested by MIE.

The total relative payoff loss ($L^{observed} - L^{MIE}$) was on average 1.39 points.[48] To get a reference for the size of this number, note that the observed loss ($L^{observed}$) of 1.90 (or 1.39+0.51) points is approximately 3.75 times as large as the MIE benchmark (L^{MIE}) of 0.51 points. The relative loss due to distortions was 1.31 points, while the relative loss due to miscommunication was 0.08 points. Thus, the distortions accounted for 94% of the overall relative loss in payoffs.[49] We highlight this as one of our main results:

Main Result 2. *Most payoff losses are due to distortions of decision rules rather than miscommunication.*

4 Discussion

Any experiment in which utility is identified with money is subject to the possibility that subjects' true utilities transform their monetary payoffs in some way. For instance, if a decision maker in our experiment is risk-averse or risk-seeking, she might have a utility function of the form $U(x) = -(-x)^{\alpha}$ over her point losses $x < 0$, where the parameter $\alpha > 0$ determines the decision maker's risk attitudes (Tversky and Kahneman, 1992). Another possibility is that the decision maker cares not only about her own monetary payoffs but also the monetary payoffs of the other players, for instance using the functional form in Levine (1998).[50] Our goal is to explore how such transformations alter the predictions in Section 2.2.

Because the principal maximizes the agents' joint payoffs, social preferences cannot explain the distortions we observe in the centralized treatments, but can lead the agents to over-coordinate relative to the self-interested benchmark under decentralization. This is a testable prediction we highlight below:

Prediction 5. If social preferences caused the distortions in Decentralized-Low and Decentralized-High, we should observe similar distortions in analogous treatments with

[48]This represents the *per-period* average. The regression results can be found in Table 23 in the appendix.

[49]Appendix A.6 provides an additional analysis of subjects' payoffs.

[50]E.g., Player 1 may be maximizing $\lambda\pi_1 + (1-\lambda)\pi_2$ and Player 2 may be maximizing $(1-\lambda)\pi_1 + \lambda\pi_2$, where $\lambda \in \left[\frac{1}{2}, 1\right]$.

complete information.

Unlike social preferences, risk aversion can generate distortions in the directions we observe both under centralization and decentralization.[51] To get some intuition for this claim, consider the case of centralization. The principal's payoff can be decomposed into two adaptation losses (one for each agent) and a coordination loss. The coordination loss is non-stochastic, while the adaptation losses depend on unknown states. If the agents report truthfully and the principal believes the messages received, the adaptation losses are also non-stochastic, conditional on the information received, and risk preferences have no bite. Noise in messages introduces uncertainty about the principal's adaptation losses. While a risk-neutral decision maker only cares about the posterior expectations of the states, a risk-averse principal also cares about the variance of her conditional expectation, and might under-coordinate to decrease this variance. Because the models of Alonso et al. (2008) and Rantakari (2008) have no closed-form solutions with risk-averse preferences, predictions have to be obtained through simulations. We do this in Appendix A.8 and argue that only 4%-17% of the observed under-coordination in the centralized treatments can be accounted for by reasonable degrees of risk aversion.[52] I.e., while risk aversion predicts distortions in the right direction, it does not seem to generate distortions of the right magnitude.[53]

Another possibility is that the observed distortions in decision rules were generated by

[51]A corollary of this claim is that risk seeking preferences generate distortions in the opposite directions and therefore cannot explain our data. There are several possible explanations for why our results differ from those of Tversky and Kahneman (1992). First, our experiment differs substantially from the choice-theoretic experiments in the prospect theory literature or related experiments such as Myagkov and Plott (1997). The noise in our game is not objective but derived from other subjects' communication rules. Second, it is possible that subjects' reference points are not zero (Kahneman and Tversky, 1979). Because incurring no losses is difficult in our environment, subjects might have formed expectations accordingly (Kőszegi and Rabin, 2006). Third, as we show below, ambiguity-aversion can generate distortions in the right direction even with moderate risk-seeking preferences.

[52]Under decentralization, reasonable degrees of risk aversion can explain 28%-50% of the under-adaptation observed in the data.

[53]In principle, risk aversion might also have influenced subjects' elicited beliefs, which we used to compute a measure of communication quality and estimate subjects' decision rules. In a regression of elicited guesses against true states, R^2 is approximately 0.7, which suggests that subjects' guesses of unknown states were quite good on average. I.e., if risk aversion biased the reported beliefs, the resulting bias was small, which is consistent with our observation that MIE rationalizes the communication data well. Second, as we show in Appendix A.3, several of our results pertaining to communication quality are robust to defining a measure of residual variance based on subjects' messages as opposed to elicited beliefs. Likewise, our main results regarding the biases in subjects' decision rules are reflected in the analysis of subjects' adaptation and coordination losses, which does not rely on belief elicitation.

ambiguity in communication. Consider, for instance, the game under centralization. If the principal is uncertain about the communication rules used by the agents, she needs to form subjective beliefs about how the states are communicated through subjects' messages. Assuming ambiguity-neutral preferences, the principal can easily form posterior beliefs $E(\theta_i|m_i)$, and ambiguity about communication rules has no predictive power. In the presence of ambiguity aversion, however, the predictions of the model change. In Appendix A.10, we perform simulations to solve the problem of an ambiguity-averse principal under centralization. The simulation assumes that the principal has preferences of the maxmin sort, where the min is taken over different beliefs about the agents' states. We find that ambiguity aversion substantially amplifies the distortions due to risk aversion. Thus, with the Tversky and Kahneman (1992)'s functional form, a risk aversion parameter of $\alpha = 2$, and ambiguity-averse preferences, the model accounts for 17% to 55% of the under-coordination observed in the data. Moreover, if the principal is ambiguity-averse, the model can generate distortions in the right direction even if her utility function is moderately risk-seeking.

Although informative, the simulations described above do not assume equilibrium behavior. We now sketch a simple variant of the models of Alonso et al. (2008) and Rantakari (2008) that allows for ambiguous communication in the presence of ambiguity-averse message receivers. Suppose that each division manager has access to an Ellsberg urn. An Ellsberg urn is an urn which contains red and black balls but whose color composition is unknown to every player. Let $\rho \in [0, 1]$ denote the fraction of red balls. Each division manager privately observes her local conditions and a draw from her Ellsberg urn before communication takes place. Ambiguous communication occurs when the sender conditions her message on the urn realization. While seemingly abstract, this construct can be used to capture both intentional and unintentional vagueness in communication.

While solving the model is beyond the scope of this paper, recent theoretical work by Kellner and Le Quement (2018) shows that ambiguous communication can be sustained in equilibria of sender-receiver games of the Crawford and Sobel (1982) type. More precisely, for any informative communication equilibrium without ambiguity aversion, there exists an ambiguous communication equilibrium which strictly Pareto-dominates it. In the latter equilibrium, communication is more informative and the receiver takes actions which are more accommodating toward the preferences of the sender. Conjecturing that similar results can be extended to the framework of Alonso et al. (2008) and Rantakari (2008), the latter observation would provide a theoretical rationale for the result in our experiment that the decision rules are more accommodating toward the message senders' private needs than predicted by the baseline model. Focusing on MIE, coordination losses would be larger than predicted in the ambiguous game under centralization while adaptation losses would be larger than predicted in the ambiguous game under decentralization. While it is not clear that the ambiguity-averse extension of the model would capture all elements of the data,[54] it provides a promising avenue for an explanation.

A simpler explanation for the observed distortions is gift exchange.[55] E.g., it might be the case that the message receivers reward the message senders for communicating private information, where the reward comes in the form of putting a higher weight on the message. Under decentralization, this would lead to a larger adaptation loss than predicted; moreover, it could lead to coordination failure (as we observe in the Decentralized-High treatment) if the weight on the other player's message is sufficiently high.[56] Under centralization, gift exchange would lead the central manager's decisions to be less coordinated than predicted, as we observe in the data.

4.1 Complete information Treatments

Consider now a complete information modification of the initial treatments where the states θ_i are commonly known. If we interpret the distortions as arising from either ambiguous communication or gift exchange, complete information should eliminate the distortions observed in the initial treatments of the experiment.[57] To shed light on the role of uncertainty in generating the distortions, we ran two additional treatments in September 2015: **Decentralized-Complete Info** ($N = 30$, one session with 10 and one with 20 subjects) and **Centralized-Complete Info** ($N = 30$, one session with 12 and one with 18 subjects). The treatments were identical to Decentralized-High and Centralized-High in all respects but the following. First, every player observed every state θ_i ($i = 1, 2$) before making any decision. Second, the players did not make any guesses about the states of other players. In particular, the agents still sent messages to each other under decentralization and to

[54]Ambiguity aversion, for instance, would bias the belief-elicitation procedure, complicating our results regarding communication quality. Moreover, it is not clear if equilibria exist of the ambiguous game where the decision makers try but fail to accommodate the message senders' needs, as we observe in the data.

[55]We thank an anonymous referee for pointing out this explanation.

[56]E.g., in the extreme case, a decision maker might completely ignore coordination, setting her decision equal to the other player's message.

[57]As pointed out by a referee, strategic uncertainty about whether or not an opponent is playing the right game could still be present in the complete information treatments.

the principal under centralization.[58] Thus, the only difference between the complete and incomplete information treatments is uncertainty about θ_i.

Because the messages are irrelevant in theory, we make no predictions about residual variance of communication in Centralized-Complete Info and Decentralized-Complete Info. The complete information decision rules are the same as those in Equation 2.4 and Equation 2.5, with the modification that each posterior belief $E[\theta_i|m_i]$ is replaced by the true value of the corresponding state θ_i. While the decision rule under decentralization is the unique equilibrium solution, the decision rule under centralization is the unique solution to the principal's decision problem:

$$d_i^D = \frac{1}{1+\gamma}\theta_i + \frac{\gamma}{1+\gamma}\theta_j, \quad i = 1, 2, \quad i \neq j. \tag{4.1}$$

$$d_i^C = \frac{1+\gamma}{1+3\gamma}\theta_i + \frac{2\gamma}{1+3\gamma}\theta_j, \quad i = 1, 2, \quad i \neq j. \tag{4.2}$$

Estimating the γ's in Equation 4.1 and Equation 4.2 using nonlinear least squares, we find a weight of 0.774 in Decentralized-Complete Info and a weight of 0.687 in Centralized-Complete Info. Neither of these estimates is significantly different from the predicted value of 0.75 ($P = 0.814$ in Decentralized-Complete Info and $P = 0.5257$ in Centralized-Complete Info).[59] We also find little significant differences in predicted and observed decision weights when the weights are estimated at the level of individual subjects. Indeed, as shown in Figure 3, the distribution of individually estimated decision weights shifts to the left under decentralization and to the right under centralization.

In Decentralized-Complete Info, the mean estimate of γ is 0.76, the median is 0.853, and neither is significantly different from 0.75.[60] In Centralized-Complete Info, the mean estimate of γ is 0.802, and the median is 1. While the mean is not significantly different from 0.75 ($P = 0.365$), the median is significantly higher ($P < 0.001$).

Thus, regardless of how the data is analyzed, the deviations from equilibrium behavior are significantly reduced in the complete information treatments. Specifically, no under-

[58] While we could have removed communication from the complete information treatments, we avoided doing this so that uncertainty and communication are not manipulated at the same time.

[59] Because we only have two sessions per treatment, the standard errors for the coefficient estimates are clustered at the level of the decision maker. The comparisons remain insignificant with session-clustered errors.

[60] $P = 0.831$ for the mean and $P = 0.414$ for the median.

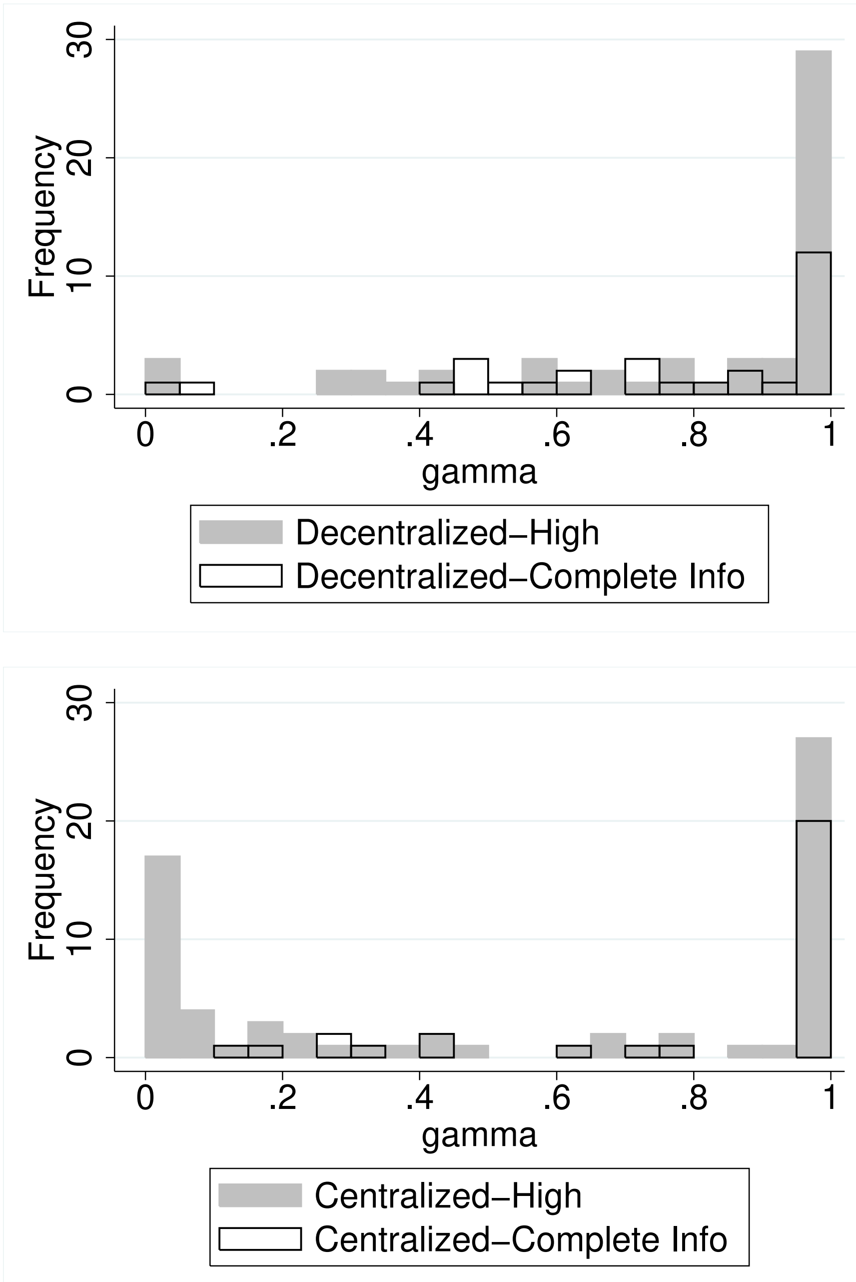


Figure 3: Distributions of decision weights, incomplete vs. complete information.

weighting of γ is observed under centralization, and no overweighting is observed under decentralization. While behavior of the median subject deviates from equilibrium under centralization, it deviates in the direction of *overweighting* the importance of coordination, the reverse of Main Result 1. Moreover, we find no significant deviations from the predicted decision weights on average. We summarize these findings as follows:

Main Result 3. *With complete information, there was no over- or underweighting of the importance of coordination on average.*

Our findings in the complete information treatments provide evidence against social preferences. They are also consistent with the hypothesis that the deviations from equilibrium observed in the initial treatments were caused by uncertainty, i.e., the hypothesis cannot be rejected. We cannot, however, identify the channel through which uncertainty distorted the decision rules in the initial treatments (e.g., ambiguous communication vs. gift exchange). This question should be addressed in future work.

5 Conclusion

An organization is often tasked with coordinating activity across multiple divisions. The presence of localized information creates uncertainty, which complicates the coordination of activity across multiple divisions. In theory, efficient decision making in multidivisional organizations can to some extent be facilitated by communication. Our results uncover an additional hurdle to efficiency, as decision makers in an experiment are more accommodating to the communicated information than predicted by standard theory.

Our experimental framework can accommodate the study of a wide array of related coordination problems. For example, Alonso et al. (2008) show that the quality of communication under decentralization can be worse if decisions are made sequentially as opposed to simultaneously. This is because the player in the role of the follower has higher incentives to misreport in an attempt to influence the decision of the leader, which makes coordination more difficult in theory. In light of our results, i.e., the players overweighting the importance of coordination under decentralization, sequential decision making might make coordination easier in practice. This is an empirical question that should be investigated. It would also be interesting to study how our results on communication and behavior are affected by asymmetries in coordination needs or partial centralization (where only one of the decisions is controlled by the principal).[61]

A different project could investigate coordination in teams with incomplete information. Thus, each player in our experiment can be identified with a team of several subjects who need to agree on which message to send and which decision to make. Feri et al. (2010) find that team decision making can lead to higher coordination on efficient outcomes, a testable prediction. An open question is whether the distortions observed in our treatments will be robust to or alleviated by decisions being made in teams. Another experiment could nest the basic framework in a repeated game. This would bring the setup closer to real world organizations in which the same agents interact for longer periods of time and allow the dynamics of communication[62] and coordination to be investigated.

[61]Both of these extensions are theoretically explored in Rantakari (2008).

[62]Will subjects communicate private information more truthfully and trust more in longer relationships? Does the quality of communication decrease over time in a finite game? Does the way in which communication feeds into subjects' decision rules change over time?

A Appendix (For Online Publication)

A.1 Residual variance of communication

Residual variances under MIE can be computed analytically. If $\gamma \in (0,1)$, it is shown in Alonso et al. (2008) that the residual variance of communication in MIE under decentralization is given by

$$E\left[(\theta_i - E[\theta_i|m_i])^2\right] = \frac{1}{12+9\gamma} \quad \text{if} \quad i = 1,2. \tag{A.1}$$

Under centralization, the residual variance of communication is given by

$$E\left[(\theta_i - E[\theta_i|m_i])^2\right] = \frac{\gamma}{9+12\gamma} \quad \text{if} \quad i = 1,2. \tag{A.2}$$

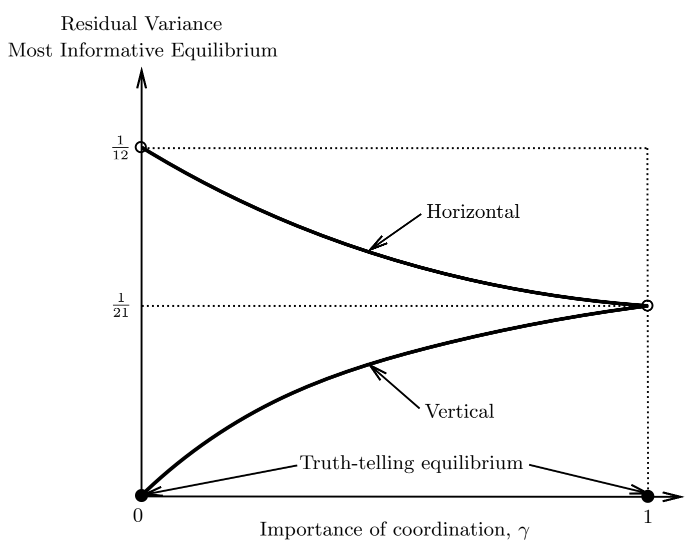


Figure 4: Predicted communication quality as a function of γ.

Figure 4 plots the residual variance of communication in MIE.

Note that when coordination is irrelevant ($\gamma = 0$), it is an equilibrium to tell the truth about one's state and set d_1 equal to θ_1 and d_2 equal to θ_2. This is true in both the centralized and the decentralized game. Because the residual variance of communication in the truth-telling equilibrium is equal to zero, the residual variance under centralization exhibits a discontinuity at $\gamma = 0$. Both residual variances also exhibit a discontinuity at $\gamma = 1$ in MIE, because truth-telling can be sustained in equilibrium when coordination is the only relevant task, given that private information has no value. In principle, these discontinuities may be behaviorally relevant. For example, it could be that when γ is low the players decide to play the game ignoring coordination, in which case full revelation is an equilibrium. This, however, is not observed in our data.

A.2 Predictions about Normalized Coordination and Adaptation Losses

Let $CL_k = E[(d_1^k - d_2^k)^2]$, $k \in \{C, D\}$, denote the normalized coordination loss. Similarly, $AL_k^i = E[(d_i^k - \theta_i^k)^2]$, $k \in \{C, D\}$, denotes the normalized adaptation loss for an arbitrary agent i, which is symmetric between agents. We have the following results.

PROPOSITION 1. For any $\gamma \in (0,1)$, $CL_C < CL_D$. Also, $\frac{dCL_C}{d\gamma} < 0$ and $\frac{dCL_D}{d\gamma} < 0$.

Proof. From the proof of Proposition 2 in Alonso et al. (2008, pag. 174), it follows that

$$CL_C = 2\frac{(1-\gamma)^2}{(1+3\gamma)^2}\frac{1+\gamma}{3+4\gamma}, \tag{A.3}$$

$$CL_D = 2(1-\gamma)^2\left[\frac{1}{3} - \gamma\frac{2}{(1+\gamma)(4+3\gamma)}\right]. \tag{A.4}$$

Differentiating (A.3) and (A.4) with respect to γ gives

$$\frac{dCL_C}{d\gamma} = -2\frac{(1+\gamma)(19+32\gamma+5\gamma^2)}{(1+3\gamma)^3(3+4\gamma)^2} < 0, \tag{A.5}$$

$$\frac{dCL_D}{d\gamma} = -\frac{2}{3}\frac{(1-\gamma)(56+64\gamma+17\gamma^2+3\gamma^3)}{(1+\gamma)^2(4+3\gamma)^2} < 0. \tag{A.6}$$

Finally, $CL_C < CL_D$, for any $\gamma \in (0,1)$, follows from Lemma 2 in Alonso et al. (2008). □

PROPOSITION 2. For any $\gamma \in (0,1)$, $AL_C^i > AL_D^i$. Also, $\frac{dAL_C^i}{d\gamma} > 0$ and $\frac{dAL_D^i}{d\gamma} > 0$.

Proof. From the proof of Proposition 2 in Alonso et al. (2008, pag. 174), it follows again that

$$AL_C^i = \frac{1}{3} - \frac{(1+\gamma)(1+6\gamma+\gamma^2)}{(1+3\gamma)^2(3+4\gamma)}, \tag{A.7}$$

$$AL_D^i = \frac{7\gamma^2+\gamma^3}{3(1+\gamma)(4+3\gamma)}. \tag{A.8}$$

Differentiating (A.7) and (A.8) with respect to γ gives

$$\frac{dAL_C^i}{d\gamma} = \frac{1+57\gamma+131\gamma^2+67\gamma^3}{(1+3\gamma)^3(3+4\gamma)^2} > 0, \tag{A.9}$$

$$\frac{dAL_D^i}{d\gamma} = \frac{\gamma}{3}\frac{56+61\gamma+14\gamma^2+3\gamma^3}{(1+\gamma)^2(4+3\gamma)^2} > 0. \tag{A.10}$$

Finally, $AL_C^i > AL_D^i$, for any $\gamma \in (0,1)$, follows from Lemma 2 in Alonso et al. (2008). □

A.3 Additional Analysis of Communication Quality

Tables 6-11 provide several robustness checks of the results in Table 2. The analysis is carried out for the first five periods of the experiment in Table 6 and the last five periods of the experiment in Table 7. Table 8 repeats the analysis in Table 2 using messages instead of guesses to form a measure of residual variance, providing a robustness check that does not rely on our belief elicitation procedure. Table 9 repeats it excluding observations in which (i) the state and message are of opposite signs or (ii) the guess and message are of opposite signs, which might be interpreted as mistakes. Because entering a minus sign requires effort, an arguably more plausible interpretation is that only observations where a minus sign is forgotten represent mistakes. Following this interpretation, Table 10 repeats the analysis excluding observations in which (i) the state is negative and the message is positive and (ii) the message is negative and the guess is positive, i.e. where one of the players "forgets" a minus sign. Table 11 runs the regression in Table 2 clustering the standard errors at the level of the message receiver (the subject making the guess). This controls for heterogeneity at the subject level without allowing for between-subject correlations.

While we find no significant treatment effects in periods 1-5 of the experiment (Table 6), this observation should be taken with caution as the effects of time on communication quality are not significant.[63] Tables 7-11 suggest that the quality of communication was significantly higher under centralization if and only if the importance of coordination was low, as predicted by MIE and reported in the main text.

A.3.1 Analysis of Heterogeneity

To study whether the effects regarding communication quality were reflected in distributions at the level of individual subjects, we generate subject "types" as follows. For each subject i, we take the observations where the subject was in the role of Player 1 and Player 2 and average out the distances $|Sent\_Message_{it} - \theta_{it}|$ between the subject's messages and states. We identify the resulting variable with the subject's "lying type."[64] Notice that the

[63] Specifically, we can run a single regression using observations in periods 1-5 and 11-15 of the experiment. If we introduce treatment dummies, a dummy for observations in later periods, and interactions between the treatment dummies and the late observations dummy, we find that none of the interactions are significant.

[64] As noted by a referee, these labels may be somewhat misleading. A subject might send a message as a recommendation of what action to take, in which case the receivers' guesses might not correspond to

	Decentralized		Centralized
$\hat{\gamma}$ when $\gamma = 0.25$	0.4954	$\not>$	0.2643
	(0.1172)		(0.0912)
	$\not\vee$		$\not\wedge$
$\hat{\gamma}$ when $\gamma = 0.75$	0.2815	$\not<$	0.670
	(0.0448)		(0.2997)
Observations		1400	

Session-clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 6: Treatment effects on residual variance of communication (periods 1-5).

	Decentralized		Centralized
$\hat{\gamma}$ when $\gamma = 0.25$	0.3701	$>^{**}$	0.1158
	(0.0722)		(0.0499)
	$\not\vee$		$\not\wedge$
$\hat{\gamma}$ when $\gamma = 0.75$	0.1914	$\not<$	0.2368
	(0.1314)		(0.1652)

Session-clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 7: Treatment effects on residual variance of communication (periods 11-15).

	Decentralized		Centralized
$\hat{\gamma}$ when $\gamma = 0.25$	0.2979	$>^{**}$	0.1036
	(0.0539)		(0.054)
	$\not\vee$		$\not\wedge$
$\hat{\gamma}$ when $\gamma = 0.75$	0.1458	$\not<$	0.2484
	(0.070)		(0.149)

Session-clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 8: Treatment effects on residual variance of communication (messages as guesses).

lying type is equal to zero if the subject's messages always corresponded to the states. Sim-

the messages. While our analysis below uses the "lying" and "mistrust" terminology, a careful reader will keep this caveat in mind.

	Decentralized		Centralized
$\hat{\gamma}$ when $\gamma = 0.25$	0.091	$>^{**}$	0.0336
	(0.022)		(0.0077)
	$\not\vee$		$\not\wedge$
$\hat{\gamma}$ when $\gamma = 0.75$	0.104	$\not<$	0.0956
	(0.0415)		(0.0461)

Session-clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 9: Treatment effects on residual variance of communication (excluding observations with sign switches).

	Decentralized		Centralized
$\hat{\gamma}$ when $\gamma = 0.25$	0.2387	$>^{****}$	0.0735
	(0.0237)		(0.0264)
	$\vee^{**}$		$\not\wedge$
$\hat{\gamma}$ when $\gamma = 0.75$	0.1163	$\not<$	0.172
	(0.0376)		(0.0906)

Session-clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 10: Treatment effects on residual variance of communication (excluding observations with missing minus sign).

	Decentralized		Centralized
$\hat{\gamma}$ when $\gamma = 0.25$	0.4272	$>^{***}$	0.1796
	(0.0686)		(0.0327)
	$\vee^{***}$		$\wedge^{***}$
$\hat{\gamma}$ when $\gamma = 0.75$	0.2164	$<^{**}$	0.3971
	(0.0315)		(0.066)

Session-clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 11: Treatment effects on residual variance of communication (errors clustered by receiver).

ilarly, averaging out the distances $|Guess_{it} - Received\_Message_{it}|$ between the subjects' elicited posterior beliefs and received messages, we obtain the subject's "mistrust type." A subject whose guesses always corresponded to the received messages had a mistrust type of zero.

	Mean	Standard Deviation	Median	Observations
Decentralized-Low	0.108	0.203	0.022	48
Decentralized-High	0.078	0.127	0.03	56
Centralized-Low	0.038	0.085	0.003	66
Centralized-High	0.088	0.157	0.011	68

(a) Lying types.

	Mean	Standard Deviation	Median	Observations
Decentralized-Low	0.058	0.147	0.008	48
Decentralized-High	0.045	0.08	0.015	56
Centralized-Low	0.045	0.085	0.008	66
Centralized-High	0.08	0.115	0.043	68

(b) Mistrust types.

Table 12: Summary statistics of lying and mistrust types.

We find that 75 subjects had a lying type of zero, 64 subjects had a mistrust type of zero, and 49 subjects had a lying type of zero *and* a mistrust type of zero.[65] I.e., the vast majority of subjects had non-zero lying and mistrust types. A more detailed description of the data is provided in Table 12, which suggests several observations that can be related to our analysis of residual variance. First, we find that the mean and median *lying type* was smaller in Centralized-Low than Decentralized-Low ($P < 0.01$ in a Wilcoxon rank-sum test).[66] Second, the difference between *mistrust types* in Centralized-Low and Decentralized-Low was small and not significant ($P = 0.889$). I.e., the lying type was smaller under centralization and the effect of centralization on the mistrust types was not significant when the importance of coordination was low, which is consistent with Prediction 1 and the results on residual variance. An increase in γ led to more lying types ($P < 0.05$) and more mistrust types ($P < 0.01$) under centralization. This is also consistent with the residual variance results, as they show no overall effect of γ in the centralized treatments. Inconsistent with the results on residual variance, γ had little effect

[65]The correlation between the lying and mistrust types has a coefficient of $\rho = 0.737$.

[66]We use the Wilcoxon rank-sum test in all statistical comparisons in this paragraph.

on subjects' types under decentralization ($P = 0.735$ for lying and $P = 0.37$ for mistrust types). The discrepancy can be reconciled by the observation that when the quality of communication is measured in terms of standard deviations $|Other\_State_{it} - Guess_{it}|$, the significant difference between these two decentralized treatments disappears. This suggests that the observed difference in residual variances of Decentralized-Low and Decentralized-High was driven by relatively large errors in guesses.

Table 13, Table 14, and Table 15 provide some robustness checks of the results reported in Table 12. In Table 13, we exclude observations with particularly large distances between states and messages and messages and guesses when computing players' types. Specifically, when computing lying types, we exclude observations in which the messages were of opposite sign of the associated states, and when computing mistrust types, we exclude observations in which the guesses were of opposite sign of the messages. In Table 14, we exclude observations in which the state was negative and the message positive or the message was negative and the guess positive. In Table 15, we compute lying and mistrust types using observations from the last five periods in the experiment, which can be viewed as a robustness check for learning effects.

Most of the statistical comparisons using the types in Tables 13-15 give qualitatively similar results to those reported in Table 12. For instance, the lying types are significantly smaller in Centralized-Low than Decentralized-Low ($P < 0.01$ leaving out observations with sign switches or omitted minus signs). While the rank-sum test shows no significant difference for later observations ($P = 0.1645$), the difference is significant according to a t-test ($P < 0.05$). Similarly, in a regression with treatment dummy variables and session-clustered errors, the coefficient on Centralized-Low is negative and strongly significant for observations in the last five periods ($P < 0.001$). As in Table 12, the mistrust types in Centralized-Low and Decentralized-Low are not significantly different ($P = 0.784$ leaving out sign switches, $P = 0.7709$ leaving out omitted minus signs, and $P = 0.813$ for later observations).

	Mean	Standard Deviation	Median	Observations
Decentralized-Low	0.059	0.139	0.01	48
Decentralized-High	0.06	0.1	0.015	56
Centralized-Low	0.013	0.04	0.001	66
Centralized-High	0.043	0.073	0.011	68

(a) Lying types.

	Mean	Standard Deviation	Median	Observations
Decentralized-Low	0.034	0.11	0.007	48
Decentralized-High	0.032	0.053	0.013	56
Centralized-Low	0.026	0.044	0.007	66
Centralized-High	0.052	0.081	0.025	68

(b) Mistrust types.

Table 13: Summary statistics of lying and mistrust types (excluding observations with sign switches).

	Mean	Standard Deviation	Median	Observations
Decentralized-Low	0.086	0.172	0.016	48
Decentralized-High	0.062	0.1	0.017	56
Centralized-Low	0.023	0.062	0.002	66
Centralized-High	0.053	0.089	0.011	68

(a) Lying types.

	Mean	Standard Deviation	Median	Observations
Decentralized-Low	0.04	0.12	0.007	48
Decentralized-High	0.033	0.057	0.013	56
Centralized-Low	0.029	0.049	0.007	66
Centralized-High	0.064	0.093	0.03	68

(b) Mistrust types.

Table 14: Summary statistics of lying and mistrust types (excluding observations with omitted minus signs).

	Mean	Standard Deviation	Median	Observations
Decentralized-Low	0.105	0.267	0	48
Decentralized-High	0.076	0.174	0	56
Centralized-Low	0.022	0.08	0	66
Centralized-High	0.058	0.162	0	68

(a) Lying types.

	Mean	Standard Deviation	Median	Observations
Decentralized-Low	0.032	0.12	0	48
Decentralized-High	0.027	0.094	0	56
Centralized-Low	0.033	0.087	0	66
Centralized-High	0.045	0.115	0	68

(b) Mistrust types.

Table 15: Summary statistics of lying and mistrust types (types estimated from observations in the last five periods of the experiment).

A.4 Robustness Checks for Section 3.2

For our econometric analysis of learning, we use the following model under centralization:

$$\begin{aligned} Decision_{it} = & \frac{(1 + \beta_0 + \beta_1 High_{it} + \beta_2 t + \beta_3 t High_{it})}{(1 + 3 * (\beta_0 + \beta_1 High_{it} + \beta_2 t + \beta_3 t High_{it})} \times Guess\_of\_the\_State_{it} + \\ & + \frac{2 * (\beta_0 + \beta_1 High_{it} + \beta_2 t + \beta_3 t High_{it})}{(1 + 3 * (\beta_0 + \beta_1 High_{it} + \beta_2 t + \beta_3 t High_{it})} \times Guess\_of\_the\_Other\_State_{it} + \epsilon_{it} \end{aligned}$$

and the following under decentralization:

$$\begin{aligned} Decision_{it} = & (1 - \beta_0 - \beta_1 High_{it} - \beta_2 t - \beta_3 t High_{it}) \times \theta_{it} + \\ & + \frac{(\beta_0 + \beta_1 High_{it} + \beta_2 t + \beta_3 t High_{it})^2}{(1 + \beta_0 + \beta_1 High_{it} + \beta_2 t + \beta_3 t High_{it})} \times Guess\_of\_the\_State_{it} + \\ & + \frac{(\beta_0 + \beta_1 High_{it} + \beta_3 t + \beta_4 t High_{it})}{(1 + \beta_0 + \beta_1 High_{it} + \beta_2 t + \beta_3 t High_{it})} \times Guess\_of\_the\_Other\_State_{it} + \epsilon_{it} \end{aligned}$$

In the baseline case (Table 5), the NLS models are identical with the exception that the coefficients involving time (β_2 and β_3) are omitted. The coefficient estimates and standard errors of the model with learning are reported in Table 16. The main text describes the results.

The remaining tables in this section report the results of robustness checks described in Section 3.2 of the main text. Table 17 is identical to Table 3, with the exception that standard errors are clustered at the level of the decision maker (as opposed to session). The models underlying Table 18, Table 19, and Table 20 are described in the last paragraph of Section 3.2.

	Decentralization	Centralization
β_0	0.684****	0.0131*
	(0.0883)	(0.00632)
β_1	0.189	0.252*
	(0.139)	(0.115)
β_2	-0.0209****	0.00193
	(0.00179)	(0.00162)
β_3	0.0298*	0.00979
	(0.0123)	(0.00983)
Observations	1560	1320

Session-clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 16: Effects of learning on distortions of decision rules (see Section A.4 for the coefficient legend).

	Decentralized	Centralized
High (dummy=1 if $\gamma = \frac{3}{4}$)	-0.00735	0.0149
	(0.0181)	(0.0166)
State (θ)	0.493****	
	(0.0427)	
Guess of the State	0.162****	0.946****
	(0.0396)	(0.0130)
Guess of the Other State	0.345****	0.0544****
	(0.0297)	(0.0130)
$\theta \times$ High	-0.270****	
	(0.0688)	
Guess of the State $\times$ High	0.0576	-0.290****
	(0.0710)	(0.0339)
Guess of the Other State $\times$ High	0.213****	0.290****
	(0.0394)	(0.0339)
Constant	0.0197	0.00615
	(0.0138)	(0.00956)
Observations	1560	1320

Session-clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 17: Estimated decision weights (standard errors clustered by subject making the decision).

	Decentralized	Centralized
$\hat{\gamma}$ when $\gamma = 0.25$	$0.538 >^{***} 0.25$	$0.055 <^{****} 0.25$
	(0.128)	(0.012)
$\hat{\gamma}$ when $\gamma = 0.75$	$1.048 >^{****} 0.75$	$0.414 <^{****} 0.75$
	(0.057)	(0.052)
Observations	1560	1320

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 18: Estimated distortions of γ (messages as proxies for beliefs).

	Centralized
$\hat{\gamma}$ when $\gamma = 0.25$	$0.052 <^{****} 0.25$
	(0.012)
$\hat{\gamma}$ when $\gamma = 0.75$	$0.443 <^{***} 0.75$
	(0.072)
Observations	1320

Session-clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 19: Estimated distortions of γ under centralization (estimated with beliefs of Player 1 and Player 2).

	Decentralized	Centralized
$\hat{\gamma}$ when $\gamma = 0.25$	$0.517 >^{***} 0.25$	$0.0296 <^{****} 0.25$
	(0.081)	(0.008)
$\hat{\gamma}$ when $\gamma = 0.75$	$0.9396 >^{***} 0.75$	$0.356 <^{****} 0.75$
	(0.07)	(0.067)
Observations	1560	1320

Subject-clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 20: Estimated distortions of γ (subject-clustered errors).

A.4.1 Analysis of Heterogeneity

Table 21 compares the within-treatment means and medians of the estimated γ's to their predicted values. We find that the mean in Decentralized-Low is significantly greater than predicted ($P < 0.001$ using a t-test), although the median is not ($P = 0.685$).[67] While the mean in Decentralized-High is not significantly greater than 0.75 ($P = 0.291$ using a t-test), the median is ($P < 0.001$). Both of the means are significantly lower than predicted in Centralized-Low and Centralized-High ($P < 0.001$ in both cases); while the median is significantly lower than predicted in Centralized-Low ($P < 0.001$), but not in Centralized-High ($P = 0.523$). The broad message of these findings is that Main Result 1 is reflected not only in overall averages, but also in distributions at the level of individual subjects.

	Mean	Standard Deviation	Median	Observations
Decentralized-Low	0.446	0.377	0.278	48
Decentralized-High	0.792	0.296	0.983	56
Centralized-Low	0.07	0.15	0.004	66
Centralized-High	0.542	0.436	0.638	68

Table 21: Distributions of individual-level estimates of γ.

[67] When comparing the medians to the associated predicted values, we run a quantile regression for each treatment. The dependent variable is the subject-level estimate of γ, and the single independent variable is a constant. We then compare the estimated constant to its predicted value using an F-test.

A.5 Omitted Figures and Tables

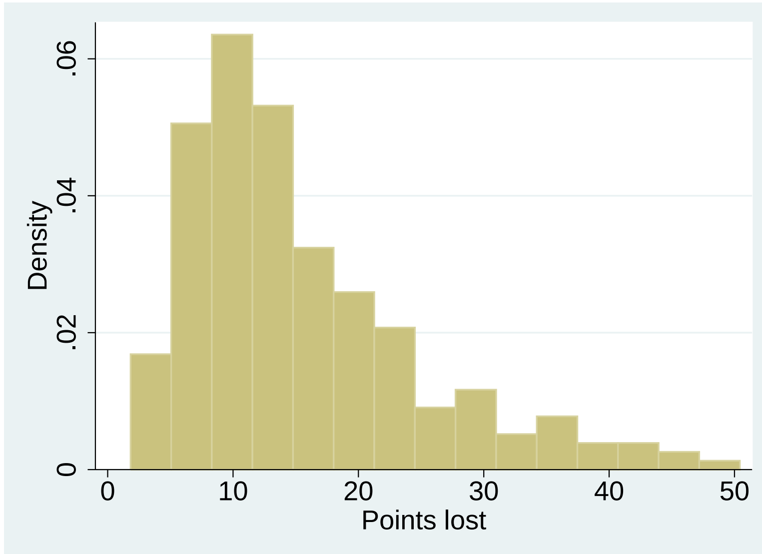


Figure 5: Points lost in the experiment by subject.

	(1)	(2)
	$(d_1 - d_2)^2$	$(d_i - \theta_i)^2$
Decentralized-High	-0.0935	0.117**
	(0.0532)	(0.0428)
Centralized-Low	0.204**	-0.145***
	(0.0700)	(0.0402)
Centralized-High	-0.0596	0.0590
	(0.0469)	(0.0741)
Constant	0.319****	0.220****
	(0.0424)	(0.0369)
Observations	1440	2880

Session-clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 22: Degrees of adaptation and coordination in different experimental treatments. The Decentralized-Low treatment serves as a baseline.

A.6 Additional Analysis of Payoffs

Recall that theory predicts expected payoffs under centralization to be higher for both chosen values of γ. The first column of Table 23 presents the results of a regression in which the total points lost by Player 1 and Player 2 from the decisions made in the game[68] are regressed against the treatment indicator variables.[69] The results show that losses are marginally lower under centralization than decentralization when γ is low ($P < 0.1$). They are also lower under decentralization when γ is high, although the difference in this case is not statistically significant ($P = 0.7738$ in a test of equality of coefficients on Decentralized-High and Centralized-High). These results are not consistent with the MIE predictions, which is not surprising given the deviations from equilibrium behavior documented above. The fact that γ is underweighted under centralization makes a principal's comparative advantage in coordination weaker. Similarly, that γ is overweighted under decentralization weakens each agent's comparative advantage in adaptation.

In the second column of Table 23, we regress the relative losses due to distortions against the treatment dummies. The estimates show that these losses were positive and significant in each of our treatments ($P < 0.001$ in every treatment). The negative coefficient on Centralized-Low ($P < 0.01$) suggests that the relative losses due to distortions were lower in this treatment than in the others. Recall that subjects in the centralized treatments overweighted the importance of adaptation. The negative coefficient suggests that in Centralized-Low, where coordination was not important, the overweighting of adaptation was less costly than it was in Centralized-High. It was also less costly than the underweighting *of adaptation* in the decentralized treatments. This is because in Decentralized-High–where the underweighting of adaptation was less costly than in Decentralized-Low–the subjects still found it difficult to coordinate their decisions. Table 24 shows that the relative loss due to miscoordination is higher in Decentralized-High than in Centralized-Low (see also Appendix A.7).

The third column of Table 23 reports the results of a regression of subjects' relative miscommunication losses against the treatment indicator variables. These results show that these losses were positive and significant in Decentralized-Low ($P < 0.05$ on the constant term) and not in any other treatment ($P > 0.1$ on the test of the constant plus any of the indicator variables being equal to zero). This is consistent with the results on communication quality reported in Section 3.1, where we find that the quality of communication is

[68]That is, excluding the points lost for guessing.

[69]Only subjects in the roles of Player 1 and Player 2 are used in this regression to avoid double-counting.

	Total points lost from the decisions $L^{observed}$	Relative payoff loss from distortions $L^{observed} - L^{reported\,beliefs}$	Relative payoff loss from communication $L^{reported\,beliefs} - L^{MIE}$
Decentralized-High	0.0667	0.346	-0.0116
	(0.281)	(0.283)	(0.0260)
Centralized-Low	-0.463*	-0.600***	0.140
	(0.242)	(0.163)	(0.143)
Centralized-High	0.154	0.353	0.101
	(0.260)	(0.214)	(0.0893)
Constant	1.959****	1.268****	0.0303**
	(0.171)	(0.157)	(0.0120)
Observations	1440	1440	1440

Session-clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 23: Payoff analysis. $L^{observed} = L_1^{observed} + L_2^{observed}$ denotes the total points lost by Player 1 and Player 2 in the game due to the decisions, $L^{reported\,beliefs} = L_1^{reported\,beliefs} + L_2^{reported\,beliefs}$ denotes the points that the team would have lost if the decision makers employed equilibrium decision rules with their reported (elicited) beliefs, and $L^{MIE} = L_1^{MIE} + L_2^{MIE}$ denotes the total points that Player 1 and Player 2 would have lost if they employed equilibrium decision rules and formed beliefs according to MIE.

significantly different from MIE in the Decentralized-Low treatment.

A.7 Additional Analysis of Adaptation and Coordination Losses

Table 24 breaks point losses of teams in different treatments of the experiment into miscomunication and miscoordination components. Thus, for example, the miscommunication component of the relative coordination loss in the treatments with $\gamma = \frac{3}{4}$ is calculated as:[70]

$$\sum_{i=1}^{2} \left\{ 3 * \left((d_i^{reported\,beliefs} - d_{-i}^{reported\,beliefs})^2 - (d_i^{MIE} - d_{-i}^{MIE})^2 \right) \right\}$$

Note that this table can be used to recover the overall relative losses due to distortions or communication reported in Table 23. For example, to compute the relative losses due to distortions in Decentralized-Low (Table 23, constant term in the second column), add the relative coordination losses due to distortions in Decentralized-Low (Table 24, first column, second row) to the relative adaptation losses due to distortions in Decentralized-Low (Table 24, first column, fifth row).

Recall from the second column of Table 23 that the relative payoff losses due to distortions were smaller in Centralized-Low than in any of the other treatments. Table 24 provides evidence for our conjecture that this was driven by coordination losses being smaller in Centralized-Low (where the overweighting of adaptation was less costly) than in Centralized-High. Thus, while the coordination loss due to distortions was greater in Centralized-High than in Centralized-Low, distortions in decision rules did not lead to adaptation losses under centralization (all $P > 0.1$). The table also provides additional evidence for Result 2: very little of the significant loss in payoffs is due to miscommunication. As discussed above, the only treatment showing significant payoff loss due to miscommunication is Decentralized-Low.

[70]The sum is necessary in the expression because the analysis of the decompositions is carried out in terms of team rather than individual payoffs.

	D-L	D-H	C-L	C-H
Relative coordination loss	0.125	1.236****	0.810****	1.533****
	(0.081)	(0.191)	(0.111)	(0.120)
Relative coordination loss (Distortions)	0.111	1.233****	0.826****	1.533****
	(0.070)	(0.200)	(0.097)	(0.120)
Relative coordination loss (Miscommunication)	0.014	0.003	-0.017	0.0001
	(0.014)	(0.012)	(0.016)	(0.001)
Relative adaptation loss	1.173****	0.397****	0.028	0.219
	(0.220)	(0.038)	(0.082)	(0.134)
Relative adaptation loss (Distortions)	1.157****	0.381****	-0.158	0.088*
	(0.221)	(0.042)	(0.106)	(0.050)
Relative adaptation loss (Miscommunication)	0.016****	0.016	0.187	0.131
	(0.002)	(0.012)	(0.134)	(0.088)
Observations	360	420	330	330

Session-clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 24: Decompositions of adaptation and coordination losses into a component due to distortions of decision weights and a component due to miscommunication. The standard errors are obtained by regressing each of the variables (e.g., relative coordination loss) against the treatment dummies.

A.8 Simulations for Risk Preferences (Centralization)

To accommodate risk-seeking as well as risk-averse preferences, we assume that the decision maker in the experiment has a utility function of the form $U(x) = -(-x)^{\alpha}$, with $\alpha > 1$ leading to risk-averse and $\alpha \in (0,1)$ to risk-seeking behavior. Suppose that authority is centralized. Let ν_i be the principal's posterior expectation about θ_i after having received a message about θ_i. Suppose that $\tilde{\nu}_i \in \{\nu_i - \epsilon, \nu_i + \epsilon\}$, with $\epsilon > 0$, $i = 1, 2$. Let $p = \text{Prob}(\tilde{\nu}_i = \nu_i + \epsilon)$. Then, $E[\tilde{\nu}_i] = \nu_i + (2p-1)\epsilon$ and $Var(\tilde{\nu}_i) = 4p(1-p)\epsilon^2$. When p is close to $\frac{1}{2}$, the distribution of ν_i is a proxy for a uniform posterior distribution around the posterior mean ν_i, as it would be in communication equilibria with risk-neutrality.[71] The parameter ϵ can be interpreted as a measure of uncertainty about the posterior expectation ν_i. The problem of the principal can therefore be written as:

$$\max_{d_1, d_2 \in \mathbb{R}} -E\left[\left((1-\gamma)(d_1 - \tilde{\nu}_1)^2 + (1-\gamma)(d_2 - \tilde{\nu}_2)^2 + 2\gamma(d_1 - d_2)^2\right)^{\alpha}\right]. \tag{A.11}$$

If the principal were risk-neutral ($\alpha = 1$), she would choose

$$d_i = \frac{1+\gamma}{1+3\gamma} E[\tilde{\nu}_i] + \frac{2\gamma}{1+3\gamma} E[\tilde{\nu}_j], \quad i = 1, 2, \ i \neq j. \tag{A.12}$$

Note that the decision rules are exactly those used by the principal in our baseline model.

We perform simulations to calculate the average distance between the principal's decisions, $|d_1 - d_2|$, for different values of ν_1, ν_2, α, and ϵ.[72] In the simulations, we assume that $p = \frac{1}{2}$[73] and consider $\nu_i \in [-0.6, 0.6]$.[74] Figure 6 shows the simulated *average* distances $D(\epsilon, \alpha) \equiv Mean_{(\nu_1,\nu_2)} \left\{|d_1^{RS} - d_2^{RS}| - |d_1^{RN} - d_2^{RN}|\right\}$ for different values of α and ϵ, with $\alpha \in [0, 1]$.[75] The figure shows that the simulated average distance is negative, which means that the decisions are on average more coordinated under risk-seeking than risk-neutrality. If we average over $\epsilon \in [0, 0.4]$, and $\alpha \in [0, 1]$, we obtain that the average distance between decisions under risk-seeking is -0.04 for $\gamma = 1/4$ and -0.01 for $\gamma = 3/4$.[76] In the experiment,

[71] Although communication equilibria could have different features under risk aversion, we make this distributional assumption for tractability.

[72] We set the grid sizes to 0.05 for ν_i, $i = 1, 2$, 0.02 for ϵ.

[73] Robustness checks suggest that the magnitude of distortions is little affected by relaxing it.

[74] The values of ν_1 and ν_2 are chosen in such a way that $\max\{|\nu_i - \epsilon|, |\nu_i + \epsilon|\} \leq 1$, $i = 1, 2$, given the simulated values of $\epsilon \in [0, 0.4]$. Varying ϵ over a smaller interval leads to smaller distortions.

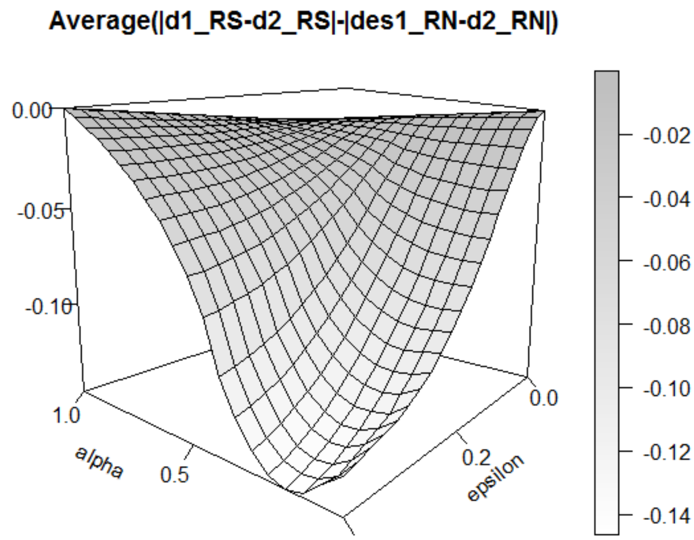
[75] More precisely, we calculate the distance D for each vector $(\alpha, \epsilon, \nu_1, \nu_2)$ and, holding α and ϵ fixed, average the distances obtained for different values of (ν_1, ν_2). The grid size for α is set at 0.05.

[76] We also performed simulations with a larger number of states, namely, $\left\{\nu_i - \epsilon, \nu_i - \frac{\epsilon}{3}, \nu_i + \frac{\epsilon}{3}, \nu_i + \epsilon\right\}$, $i = 1, 2$. We found similar qualitative and quantitative results.

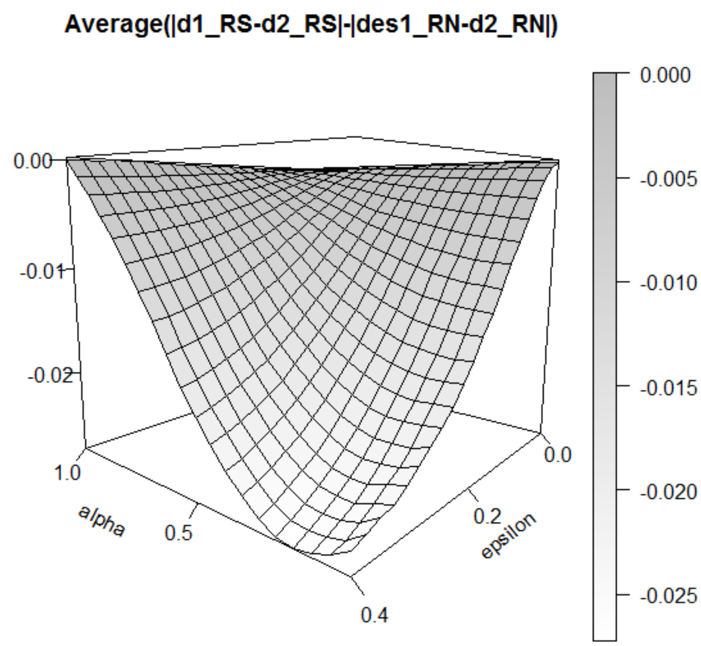
the average absolute distance between the observed and risk-neutral equilibrium decisions, $|d_1^{Observed} - d_2^{Observed}| - |d_1^{Eq} - d_2^{Eq}|$, is approximately 0.29 for Centralized-Low and 0.22 for Centralized-High. Based on these simulation results, we conclude that risk-seeking cannot explain the over-coordination observed in the centralized treatments in the data.

Simulation results for risk-averse preferences are shown in Figure 7. The figure gives us a rough idea of how much risk aversion is necessary to generate distortions of the order observed in the experiment. With $\alpha \in [1, 5]$,[77] we obtain that the average difference in the distances is 0.05 for $\gamma = 1/4$ and 0.01 for $\gamma = 3/4$. Although the simulated distortions go in the same direction as what we observe in our data, the magnitudes are of a different order even with highly unreasonable degrees of risk aversion. For example, averaging over $\alpha \in [10, 20]$ only raises the average between distances to 0.098 for $\gamma = 1/4$ and 0.029 $\gamma = 3/4$. We performed simulations with alternative, standard, utility functions such as the log and CRRA and obtained similar results. This shows that risk aversion can partly explain the distortions observed in the centralized treatments with incomplete information but cannot fully accommodate them.

[77] The grid size for α was increased to 0.1 due to the larger parameter interval.

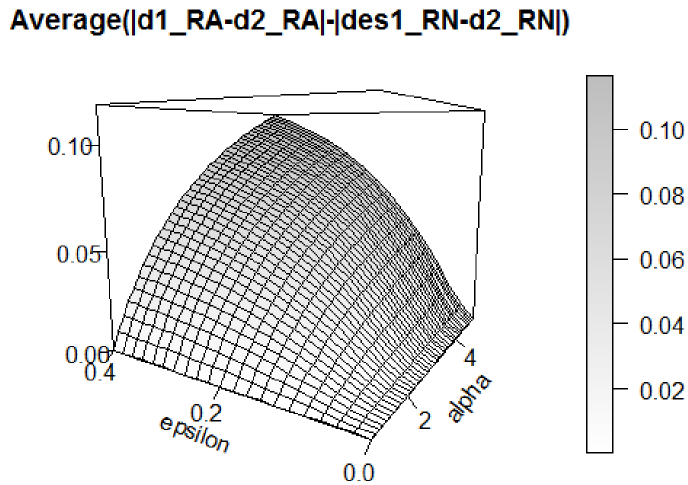


(a) Comparison of average distances between optimal risk-seeking and risk-neutral decisions, $|d_1^{RS} - d_2^{RS}| - |d_1^{RN} - d_2^{RN}|$ for $\gamma = \frac{1}{4}$. Each point corresponds to the average over $(\nu_1, \nu_2) \in [-0.6, 0.6]^2$ with a grid of size 0.05. The grid size for α is 0.05.

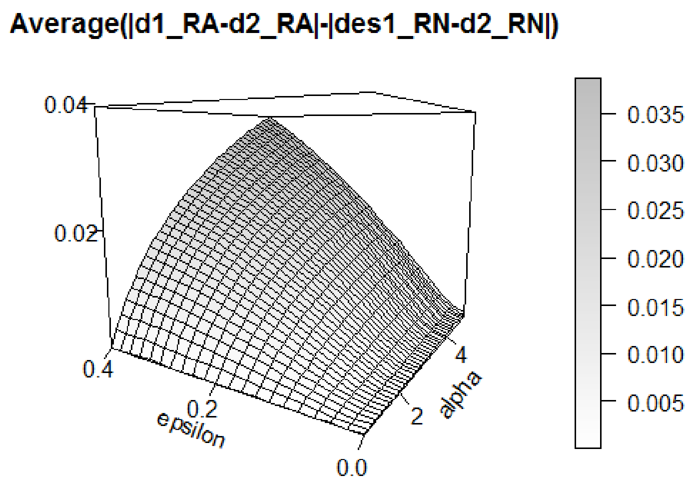


(b) Comparison of average distances between optimal risk-seeking and risk-neutral decisions, $|d_1^{RS} - d_2^{RS}| - |d_1^{RN} - d_2^{RN}|$ for $\gamma = \frac{3}{4}$. Each point corresponds to the average over $(\nu_1, \nu_2) \in [-0.6, 0.6]^2$ with a grid of size 0.05. The grid size for α is 0.05.

Figure 6: The effect of risk-seeking on coordination behavior in centralized coordination games.



(a) Comparison of average distances between optimal risk-averse and risk-neutral decisions, $|d_1^{RA} - d_2^{RA}| - |d_1^{RN} - d_2^{RN}|$ for $\gamma = \frac{1}{4}$. Each point corresponds to the average over $(\nu_1, \nu_2) \in [-0.6, 0.6]^2$ with a grid of size 0.05.



(b) Comparison of average distances between optimal risk-averse and risk-neutral decisions, $|d_1^{RA} - d_2^{RA}| - |d_1^{RN} - d_2^{RN}|$ for $\gamma = \frac{3}{4}$. Each point corresponds to the average over $(\nu_1, \nu_2) \in [-0.6, 0.6]^2$ with a grid of size 0.05.

Figure 7: The effect of risk aversion on coordination behavior in centralized coordination games.

A.9 Simulations for Risk Preferences (Decentralization)

Under decentralization, we can without loss of generality consider the decision problem of Player 1. Player 1 observes her own local conditions θ_1 and needs to make a single decision without knowing the decision made by Player 2. Let us reformulate the problem assuming that the decision of Player 2, $\tilde{d}_2$, is random from Player 1's perspective and could take on the value $d_2 + \epsilon$ with probability p, or $d_2 - \epsilon$ otherwise, where $d_2 \in (-1, 1)$ and $\epsilon \in (0, 1 - |d_2|)$. We interpret d_2 as the expected decision of Player 2 from Player 1's perspective.

Given a risk aversion coefficient α, Player 1's decision problem can be written as

$$\max_{d_1 \in \mathbb{R}} -E\left[\left((1-\gamma)(d_1 - \theta_1)^2 + \gamma(d_1 - \tilde{d}_2)^2\right)^{\alpha}\right]. \tag{A.13}$$

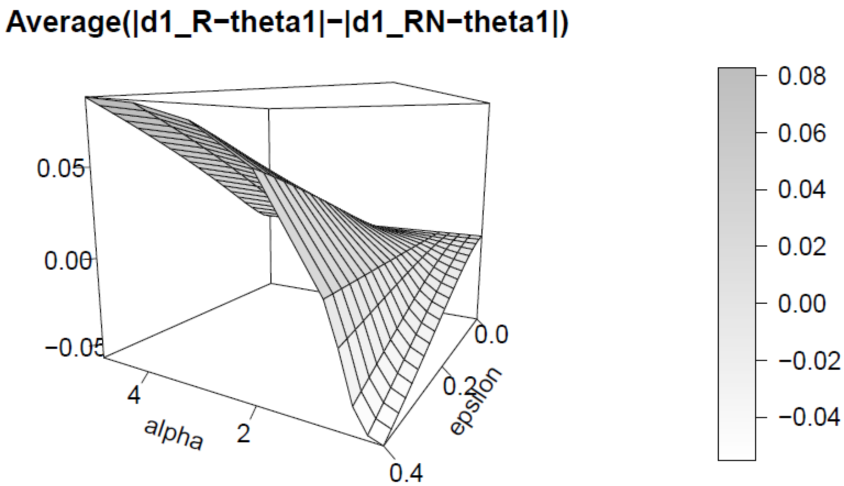
If Player 1 were risk-neutral ($\alpha = 1$), she would choose

$$d_1 = (1-\gamma)\theta_1 + \gamma E[\tilde{d}_2]. \tag{A.14}$$

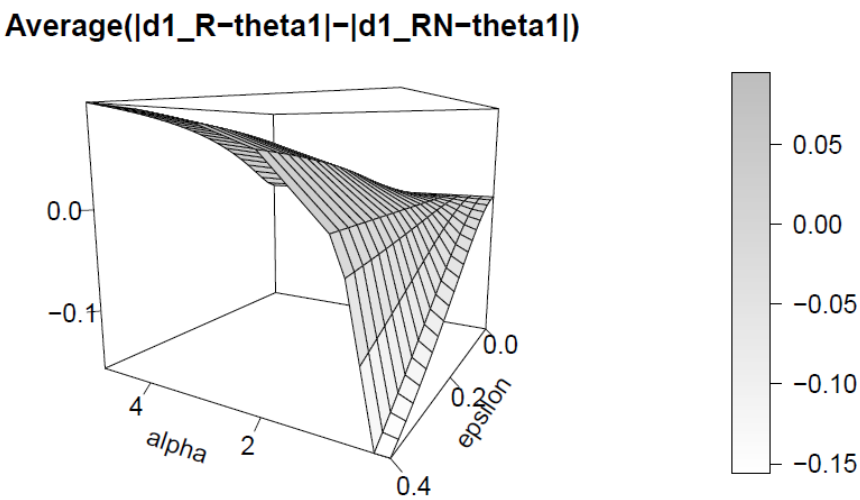
Note that this decision rule is the same as the one used by Player 1 in the baseline model, given our interpretation of d_2.

We perform simulations to calculate the degree of adaptation, $|d_1 - \theta_1|$, for different values of θ_1, d_2, α, and ϵ. In the simulations, we assume that $p = \frac{1}{2}$ and consider values of $\theta_1 \in [-1, 1]$, $d_2 \in [-0.6, 0.6]$, and $\epsilon \in [0, 0.4]$.[78] Figure 8 shows the simulated average distances $D(\epsilon, \alpha) \equiv Mean_{(\theta_1, d_2)} \left\{|d_1^R - \theta_1| - |d_1^{RN} - \theta_1|\right\}$ for different values of α and ϵ. The figure shows that the decisions are on average more adapted under risk-seeking than risk neutrality, and more adapted under risk neutrality than under risk aversion. More precisely, averaging over $\epsilon \in [0, 0.4]$ and $\alpha \in \{0.2, 0.4, 0.6, 0.8\}$, for a risk seeking decision maker, we obtain that the average distances are approximately -0.02 for $\gamma = 1/4$, and -0.05 for $\gamma = 3/4$. For degrees of risk aversion in the set $\{2, 3, 4, 5\}$, the same average leads to 0.036 for $\gamma = 1/4$, and 0.05 for $\gamma = 3/4$. For comparison, the average distance between decisions and states in the data is approximately 0.128 for $\gamma = 1/4$, and 0.10 for $\gamma = 3/4$. Thus, risk aversion explains the direction of the observed distortions under decentralization. It is also provides quantitative benchmarks that are closer to the data than their counterparts in the centralized case.

[78]The grids for θ_1, d_2, and ϵ are 0.01, 0.01, and 0.02, respectively.



(a) Comparison of average distances between optimal risky and risk neutral level of adaptation, $|d_1^R - \theta_1| - |d_1^{RN} - \theta_1|$ for $\gamma = \frac{1}{4}$, different attitudes toward risk, $\alpha \in \{0.2, 0.4, 0.6, 0.8, 1, 2, 3, 4, 5\}$, and different values of $\epsilon \in [0, 0.4]$ with grid of size 0.02. Each point corresponds to the average over $(\theta_1, d_2) \in [-1, 1] \times [-0.6, 0.6]$ with a grid of size 0.01.



(b) Comparison of average distances between optimal risky and risk neutral level of adaptation, $|d_1^R - \theta_1| - |d_1^{RN} - \theta_1|$ for $\gamma = \frac{3}{4}$, different attitudes toward risk, $\alpha \in \{0.2, 0.4, 0.6, 0.8, 1, 2, 3, 4, 5\}$, and different values of $\epsilon \in [0, 0.4]$ with grid of size 0.02. Each point corresponds to the average over $(\theta_1, d_2) \in [-1, 1] \times [-0.6, 0.6]$ with a grid of size 0.01.

Figure 8: The effect of attitudes toward risk on the degree of adaptation in decentralized coordination games.

A.10 Simulations for Ambiguity Preferences (Centralization)

We now use simulations similar to those described in Sections A.8 and A.9 to argue that strategic uncertainty about communication rules combined with ambiguity-aversion can generate distortions of larger magnitudes than those generated by risk-aversion alone. Moreover, ambiguity-aversion can generate distortions in the right direction even with risk-seeking preferences. To see this, assume that the principal solves the following optimization problem:

$$\max_{d_1,d_2\in\mathbb{R}} \min_{\mu\in\{(p,1-p),(1-p,p)\}} -E_\mu\left[\left((1-\gamma)(d_1-\tilde{\nu}_1)^2+(1-\gamma)(d_2-\tilde{\nu}_2)^2+2\gamma(d_1-d_2)^2\right)^\alpha\right].$$

Here, μ indexes the principal's belief system, which specifies beliefs both about ν_1 and about ν_2.[79]

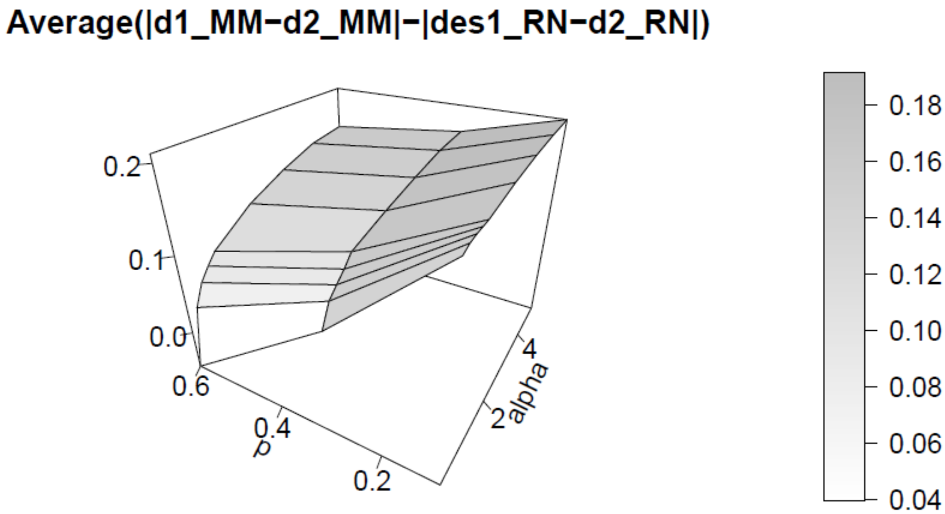
The belief system can be either $(p,1-p)$ or $(1-p,p)$. If $\mu=(p,1-p)$, p is the probability that ν_1 is high as well as the probability that ν_2 is low.[80] If $\mu=(1-p,p)$, then p is the probability that ν_1 is low as well as the probability that ν_2 is high. Thus, for any $p\neq 1/2$, the principal considers two belief systems: one in which the probability that ν_1 is high is greater than the probability that ν_2 is high, and another in which the probability that ν_2 is high is greater than the probability that ν_1 is high. Intuitively, for any (ν_1,ν_2), the principal posterior beliefs can take on one of four values: $(\nu_1-\epsilon,\nu_2-\epsilon)$, $(\nu_1-\epsilon,\nu_2+\epsilon)$, $(\nu_1+\epsilon,\nu_2-\epsilon)$, or $(\nu_1+\epsilon,\nu_2+\epsilon)$. The principal will use one of two belief systems $(p,1-p)$ and $(1-p,p)$ to compute her expected utility. Ambiguity-aversion will make the principal select the belief system under which "bad" posteriors–posteriors where beliefs about ν_1 and ν_2 are further apart–are more likely. In the simulation, we consider three possible values for $p\in\{0.1,0.3,0.6\}$. To complete the description of the simulation, we assume that both belief systems are equally likely, so that an ambiguity neutral decision maker will have a posterior belief equal to $1/2$ for any of our possible values of p.

Our simulation results with different values of p and α are reported in Figure 9 in the appendix. These results show that introducing ambiguity-aversion amplifies the distortions caused by risk aversion considerably. Thus, even with risk neutrality, that is, $\alpha=1$, we obtain that the average difference in the distances, over our simulated values of p, is 0.1369 for $\gamma=1/4$ and 0.031 for $\gamma=3/4$. Increasing the risk aversion coefficient to $\alpha=2$ increases the average difference in distance to 0.1547 for $\gamma=1/4$ and 0.039 for $\gamma=3/4$, thus more than tripling the average distances compared to an ambiguity neutral but risk averse agent

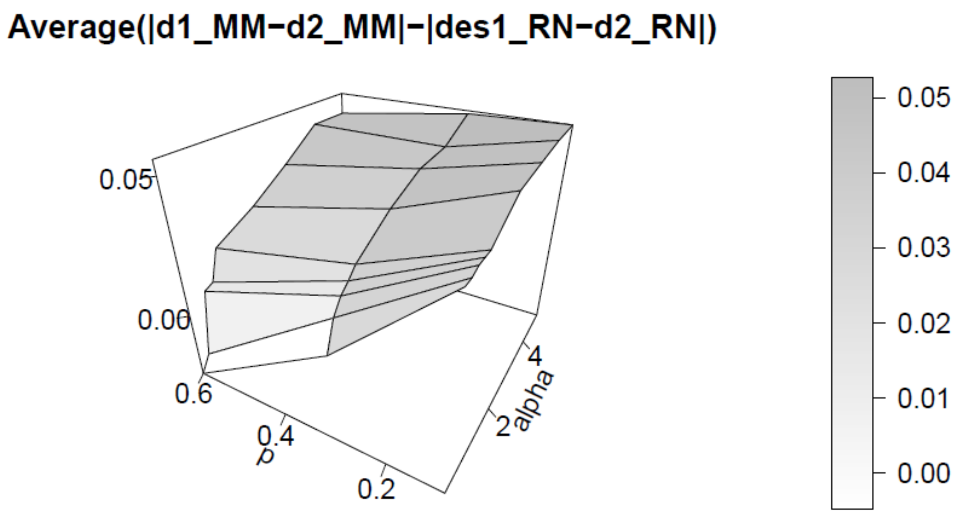
[79] Recall that we assume ν_1 and ν_2 are independent.

[80] Formally, $p=\text{Prob}(\tilde{\nu}_1=\nu_1+\epsilon)$ and $p=\text{Prob}(\tilde{\nu}_1=\nu_1-\epsilon)$.

with the same attitudes toward risk. We conclude that reasonable degrees of risk aversion (i.e., $\alpha = 2$), coupled with extreme aversion to ambiguity, can account for 17% to 55% of the distortions observed in the data. Moreover, note that when p is either sufficiently low or sufficiently high, the simulated distortions are quantitatively close to those for an ambiguity neutral decision maker for values of α in the upper part of the interval $[0, 1]$. This suggests that ambiguity-aversion can generate a reasonable fit to the data even with moderate risk-seeking preferences.



(a) Comparison of average distances between optimal maxmin and risk/ambiguity-neutral decisions, $|d_1^{MM} - d_2^{MM}| - |d_1^{RN} - d_2^{RN}|$ for $\gamma = \frac{1}{4}$, different degrees of risk aversion α, and different distribution parameters p. Each point corresponds to the average over $(\nu_1, \nu_2) \in [-0.6, 0.6]^2$ with a grid of size 0.05. The grid size for the decisions is 0.05, and the value of $\epsilon = 0.4$.



(b) Comparison of average distances between optimal maxmin and risk/ambiguity-neutral decisions, $|d_1^{MM} - d_2^{MM}| - |d_1^{RN} - d_2^{RN}|$ for $\gamma = \frac{3}{4}$, different degrees of risk aversion α, and different distribution parameters p. Each point corresponds to the average over $(\nu_1, \nu_2) \in [-0.6, 0.6]^2$ with a grid of size 0.05. The grid size for the decisions is 0.05, and the value of $\epsilon = 0.4$.

Figure 9: The effect of ambiguity-aversion on coordination behavior in centralized coordination games.

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