Supplementary Material

Supplement to "Communication and behavior in organizations: An experiment"

(*Quantitative Economics*, Vol. 10, No. 2, May 2019, 775–801)

Piotr Evdokimov
CIE, ITAM

Umberto Garfagnini
School of Economics, University of Surrey

Appendix A: Residual variance of communication

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

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

Under centralization, the residual variance of communication is given by

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

Figure S.1 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.

Appendix B: 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

Piotr Evdokimov: pevdokim@gmail.com
Umberto Garfagnini: u.garfagnini@surrey.ac.uk

 https://doi.org/10.3982/QE809

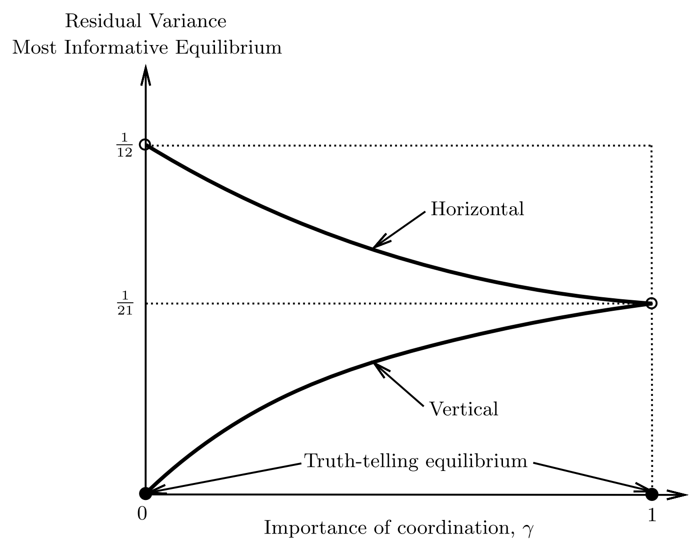


FIGURE S.1. Predicted communication quality as a function of γ.

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, Dessein, and Matouschek (2008, p. 174), it follows that

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

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

Differentiating (B.1) and (B.2) with respect to γ gives

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

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

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

Proposition 2. *For any* $\gamma \in (0,1)$, $AL^i_C > AL^i_D$. *Also,* $\frac{dAL^i_C}{d\gamma} > 0$ *and* $\frac{dAL^i_D}{d\gamma} > 0$.

Proof. From the proof of Proposition 2 in Alonso, Dessein, and Matouschek (2008, p. 174), it follows again that

$$AL^i_C = \frac{1}{3} - \frac{(1+\gamma)\big(1+6\gamma+\gamma^2\big)}{(1+3\gamma)^2(3+4\gamma)}, \tag{B.5}$$

$$AL^i_D = \frac{7\gamma^2+\gamma^3}{3(1+\gamma)(4+3\gamma)}. \tag{B.6}$$

Differentiating (B.5) and (B.6) with respect to γ gives

$$\frac{dAL^i_C}{d\gamma} = \frac{1+57\gamma+131\gamma^2+67\gamma^3}{(1+3\gamma)^3(3+4\gamma)^2} > 0, \tag{B.7}$$

$$\frac{dAL^i_D}{d\gamma} = \frac{\gamma}{3}\frac{56+61\gamma+14\gamma^2+3\gamma^3}{(1+\gamma)^2(4+3\gamma)^2} > 0. \tag{B.8}$$

Finally, $AL^i_C > AL^i_D$, for any $\gamma \in (0,1)$, follows from Lemma 2 in Alonso, Dessein, and Matouschek (2008). □

Appendix C: Additional analysis of communication quality

Tables S.1–S.6 provide several robustness checks of the results in Table 2 of the main text. The analysis is carried out for the first five periods of the experiment in Table S.1 and the last 5 periods of the experiment in Table S.2. Table S.3 repeats the analysis in Table 2 of the main text 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 S.4 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

Table S.1. Treatment effects on residual variance of communication (periods 1–5).

	Decentralized		Centralized
$\gamma = 0.25$	0.4954	$>$	0.2643
	(0.1172)		(0.0912)
	$\vee$		$\wedge$
$\gamma = 0.75$	0.2815	$<$	0.670
	(0.0448)		(0.2997)
Observations		1400	

Note: Session-clustered standard errors in parentheses.

Table S.2. Treatment effects on residual variance of communication (periods 11–15).

	Decentralized		Centralized
$\gamma = 0.25$	0.3701	$>$	0.1158
	(0.0722)		(0.0499)
	$\vee$		$\wedge$
$\gamma = 0.75$	0.1914	$<$	0.2368
	(0.1314)		(0.1652)

Note: Session-clustered standard errors in parentheses.

represent mistakes. Following this interpretation, Table S.5 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, that is, where one of the players "forgets" a minus sign. Table S.6 runs the regression in Table 2 of the main text 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 S.1), this observation should be taken with caution as the effects of time on communication quality are not significant.[1] Tables S.2–S.6 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.

C.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

Table S.3. Treatment effects on residual variance of communication (messages as guesses).

	Decentralized		Centralized
$\gamma = 0.25$	0.2979	$>$	0.1036
	(0.0539)		(0.054)
	$\vee$		$\wedge$
$\gamma = 0.75$	0.1458	$<$	0.2484
	(0.070)		(0.149)

Note: Session-clustered standard errors in parentheses.

[1] 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.

TABLE S.4. Treatment effects on residual variance of communication (excluding observations with sign switches).

	Decentralized		Centralized
$\gamma = 0.25$	0.091	>	0.0336
	(0.022)		(0.0077)
	∨		∧
$\gamma = 0.75$	0.104	<	0.0956
	(0.0415)		(0.0461)

Note: Session-clustered standard errors in parentheses.

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."[2] Notice that the lying type is equal to zero if the subject's messages always corresponded to the states. Similarly, 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.

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.[3] That is, the vast majority of subjects had nonzero lying and mistrust types. A more detailed description of the data is provided in Table S.7, 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).[4] Second, the difference between *mistrust types* in Centralized-

TABLE S.5. Treatment effects on residual variance of communication (excluding observations with missing minus sign).

	Decentralized		Centralized
$\gamma = 0.25$	0.2387	>	0.0735
	(0.0237)		(0.0264)
	∨		∧
$\gamma = 0.75$	0.1163	<	0.172
	(0.0376)		(0.0906)

Note: Session-clustered standard errors in parentheses.

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

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

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

TABLE S.6. Treatment effects on residual variance of communication (errors clustered by receiver).

	Decentralized		Centralized
$\gamma = 0.25$	0.4272	$>$	0.1796
	(0.0686)		(0.0327)
	$\vee$		$\wedge$
$\gamma = 0.75$	0.2164	$<$	0.3971
	(0.0315)		(0.066)

Note: Session-clustered standard errors in parentheses.

Low and Decentralized-Low was small and not significant ($P = 0.889$). That is, 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 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 S.8, Table S.9, Table S.10, and Table S.11 provide some robustness checks of the results reported in Table S.7. In Table S.8, we exclude observations with particularly large distances between states and messages and messages and guesses when comput-

TABLE S.7. Summary statistics of lying and mistrust types.

	Mean	Standard Deviation	Median	Observations
		(a) Lying types		
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
		(b) Mistrust types		
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

Table S.8. Summary statistics of lying and mistrust types (excluding observations with sign switches).

	Mean	Standard Deviation	Median	Observations
		(a) Lying types		
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
		(b) Mistrust types		
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

ing 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 S.9, we exclude observations in which the state was negative and the message positive or the message was negative and the guess positive. In Table S.10, 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. In Table S.11, we compute the fractions of lying messages and mistrusting guesses in each of the treatments.[5]

Table S.9. Summary statistics of lying and mistrust types (excluding observations with omitted minus signs).

	Mean	Standard Deviation	Median	Observations
		(a) Lying types		
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
		(b) Mistrust types		
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

[5]As before, a message is defined as lying if it is not equal to the state, while a guess is defined as mistrusting if it is not equal to the message. For each subject, we first averaged each dummy variable to compute the subject's percentage of lying messages and mistrusting guesses. The table reports summary statistics of these subject-level percentages by treatment.

TABLE S.10. Summary statistics of lying and mistrust types (types estimated from observations in the last five periods of the experiment).

	Mean	Standard Deviation	Median	Observations
		(a) Lying types		
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
		(b) Mistrust types		
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	0.105	0	68

Most of the statistical comparisons using the types in Tables S.8–S.10 give qualitatively similar results to those reported in Table S.7. 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 ($P < 0.001$). The fraction of lying messages is also smaller in Centralized-Low than Decentralized low, although the difference is only marginally significant in this case ($P < 0.1$). As in Table S.7, 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). The fractions of mistrusting messages also do not significantly differ across these two treatments ($P = 0.9675$).

TABLE S.11. Percentages of lying messages and mistrusting guesses.

	Mean	Standard Deviation	Median	Observations
		(a) Lying messages		
Decentralized-Low	0.375	0.352	0.267	48
Decentralized-High	0.39	0.381	0.333	56
Centralized-Low	0.284	0.366	0.091	66
Centralized-High	0.415	0.396	0.273	68
		(b) Mistrusting guesses		
Decentralized-Low	0.294	0.342	0.1	48
Decentralized-High	0.306	0.340	0.133	56
Centralized-Low	0.301	0.347	0.13	66
Centralized-High	0.396	0.361	0.317	68

Appendix D: Robustness checks for Section 3.2

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

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

and the following under decentralization:

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

In the baseline case (Table 5 in the main text), 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 S.12. The main text describes the results.

The remaining tables in this part of the appendix report the results of robustness checks described in Section 3.2 of the main text. Table S.13 is identical to Table 3 in the main text, with the exception that standard errors are clustered at the level of the decision maker (as opposed to session). The models underlying Table S.14, Table S.15, and Table S.16 are described in the last paragraph of Section 3.2 of the main text.

D.1 *Analysis of heterogeneity*

Table S.17 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 ($P = 0.685$).[6] 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

[6]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.

TABLE S.12. Effects of learning on distortions of decision rules (see Appendix D for the coefficient legend).

	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

Note: Session-clustered standard errors in parentheses.

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.

TABLE S.13. Estimated decision weights (standard errors clustered by subject making the decision).

	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 × High	0.0576	−0.290
	(0.0710)	(0.0339)
Guess of the other state × High	0.213	0.290
	(0.0394)	(0.0339)
Constant	0.0197	0.00615
	(0.0138)	(0.00956)
Observations	1560	1320

Note: Subject-clustered standard errors in parentheses.

TABLE S.14. Estimated distortions of γ (messages as proxies for beliefs).

	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

Note: Standard errors in parentheses.

TABLE S.15. Estimated distortions of γ under centralization (estimated with beliefs of Player 1 and Player 2).

	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

Note: Session-clustered standard errors in parentheses.

TABLE S.16. Estimated distortions of γ (subject-clustered errors).

	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

Note: Subject-clustered standard errors in parentheses.

TABLE S.17. Distributions of individual-level estimates of γ.

	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

Appendix E: Omitted figures and tables

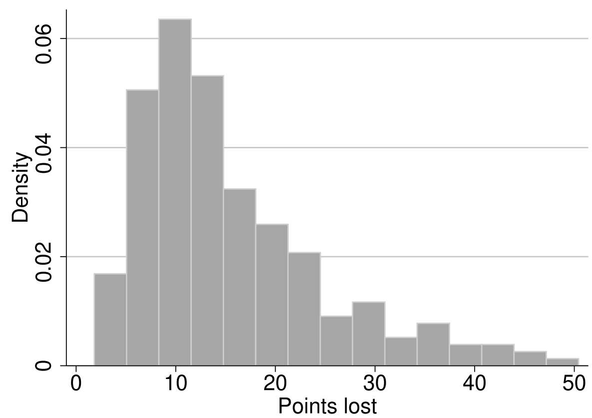


Figure S.2. Points lost in the experiment by subject.

Table S.18. Degrees of adaptation and coordination in different experimental treatments. The decentralized-low treatment serves as a baseline.

	(1) $(d_1 - d_2)^2$	(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

Note: Session-clustered standard errors in parentheses.

Appendix F: 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 S.19 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[7]

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

TABLE S.19. Payoff analysis. $L^{\text{observed}} = L_1^{\text{observed}} + L_2^{\text{observed}}$ denotes the total points lost by Player 1 and Player 2 in the game due to the decisions, $L^{\text{reported beliefs}} = L_1^{\text{reported beliefs}} + L_2^{\text{reported beliefs}}$ denotes the points that the team would have lost if the decision makers employed equilibrium decision rules with their reported (elicited) beliefs, and $L^{\text{MIE}} = L_1^{\text{MIE}} + L_2^{\text{MIE}}$ 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.

	Total points lost from the decisions L^{observed}	Relative payoff loss from distortions $L^{\text{observed}} - L^{\text{reported beliefs}}$	Relative payoff loss from communication $L^{\text{reported beliefs}} - L^{\text{MIE}}$
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

Note: Session-clustered standard errors in parentheses.

are regressed against the treatment indicator variables.[8] 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 S.19, 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 S.20 shows that the relative loss due to miscoordination is higher in Decentralized-High than in Centralized-Low (see also Appendix G).

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

TABLE S.20. 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.

	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

Note: Session-clustered standard errors in parentheses.

The third column of Table S.19 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 of the main text, where we find that the quality of communication is significantly different from MIE in the Decentralized-Low treatment.

Appendix G: Additional analysis of adaptation and coordination losses

Table S.20 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[9]

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

Note that this table can be used to recover the overall relative losses due to distortions or communication reported in Table S.19. For example, to compute the relative losses

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

due to distortions in Decentralized-Low (Table S.19, constant term in the second column), add the relative coordination losses due to distortions in Decentralized-Low (Table S.20, first column, second row) to the relative adaptation losses due to distortions in Decentralized-Low (Table S.20, first column, fifth row).

Recall from the second column of Table S.19 that the relative payoff losses due to distortions were smaller in Centralized-Low than in any of the other treatments. Table S.20 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 Main 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.

Appendix H: 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 $\text{Var}(\tilde{\nu}_i) = 4p(1 - p)\epsilon^2$. 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.[10] 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

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

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

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

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

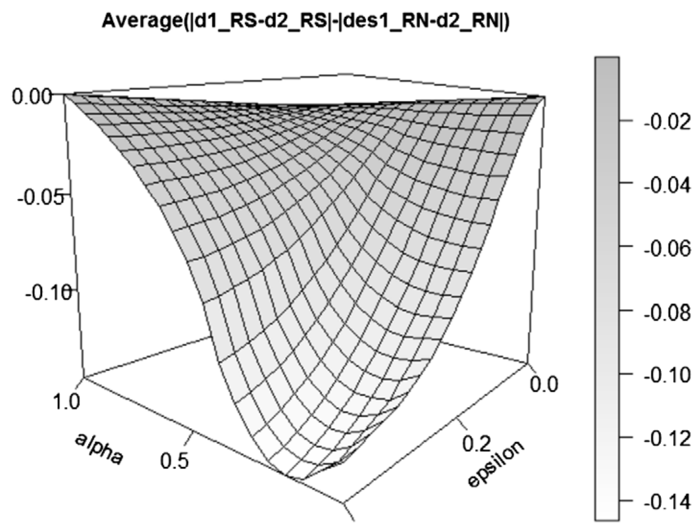
We perform simulations to calculate the average distance between the principal's decisions, $|d_1 - d_2|$, for different values of ν_1, ν_2, α, and ϵ.[11] In the simulations, we assume that $p = \frac{1}{2}$[12] and consider $\nu_i \in [-0.6, 0.6]$.[13] Figure S.3 shows the simulated *average* distances $D(\epsilon, \alpha) \equiv \text{Mean}_{(\nu_1, \nu_2)}\{|d_1^{\text{RS}} - d_2^{\text{RS}}| - |d_1^{\text{RN}} - d_2^{\text{RN}}|\}$ for different values of α

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

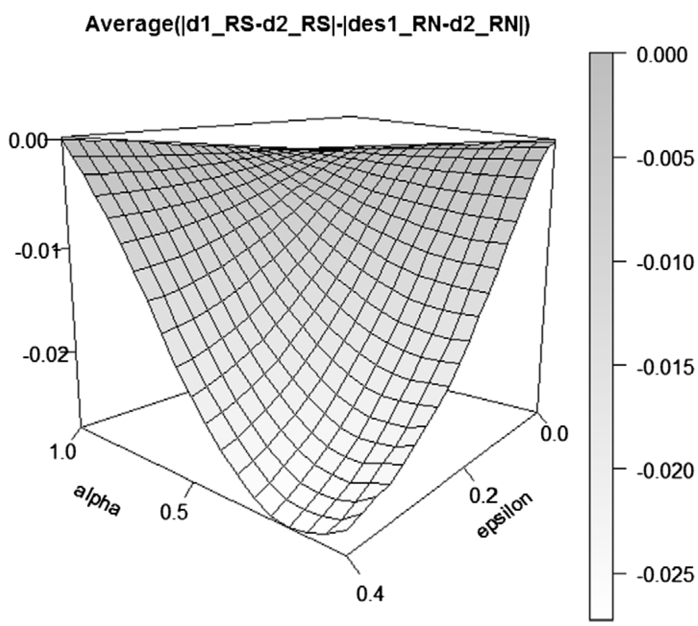
[11] We set the grid sizes to 0.05 for ν_i, $i = 1, 2$, 0.02 for ϵ.

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

[13] 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.



(a) Comparison of average distances between optimal risk-seeking and risk-neutral decisions, $|d_1^{\mathrm{RS}} - d_2^{\mathrm{RS}}| - |d_1^{\mathrm{RN}} - d_2^{\mathrm{RN}}|$ 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, $|d_1^{\mathrm{RS}} - d_2^{\mathrm{RS}}| - |d_1^{\mathrm{RN}} - d_2^{\mathrm{RN}}|$ 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 S.3. The effect of risk-seeking on coordination behavior in centralized coordination games.

and ϵ, with $\alpha \in [0, 1]$.[14] 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 $\gamma = 3/4$.[15] In the experiment, the average absolute distance between the observed and risk-neutral equilibrium decisions, $|d_1^{\text{Observed}} - d_2^{\text{Observed}}| - |d_1^{\text{Eq}} - d_2^{\text{Eq}}|$, 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 S.4. 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 $\alpha \in [1, 5]$,[16] 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.

Appendix I: 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

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

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

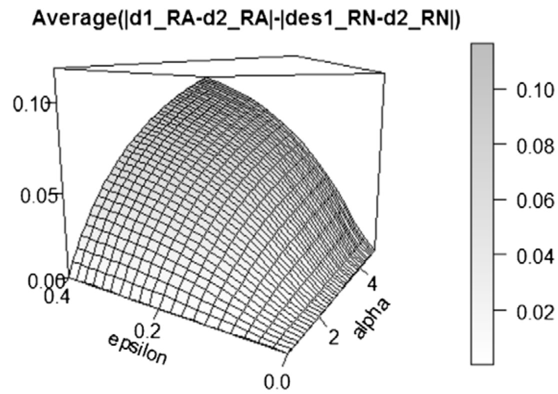
$$d_1 = (1-\gamma)\theta_1 + \gamma E[\tilde{d}_2]. \tag{I.2}$$

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.

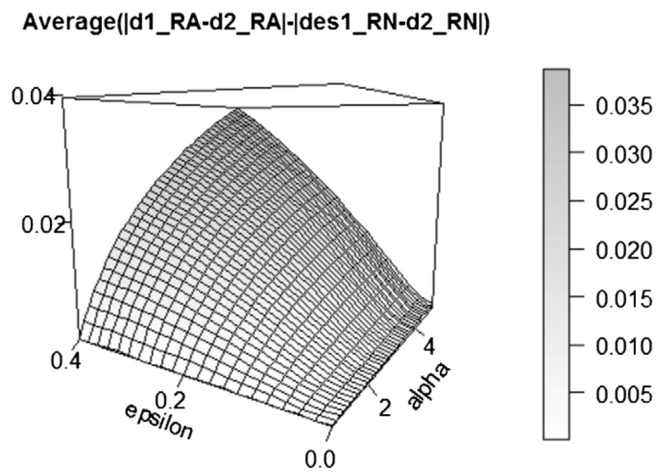
[14] More precisely, we calculate the distance D for each vector $(\alpha, \epsilon, \nu_1, \nu_2)$ and, holding α and ϵ fixed, average the distances obtained for different values of (ν_1, ν_2). The grid size for α is set at 0.05.

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

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



(a) Comparison of average distances between optimal risk-averse and risk-neutral decisions, $|d_1^{\mathrm{RA}} - d_2^{\mathrm{RA}}| - |d_1^{\mathrm{RN}} - d_2^{\mathrm{RN}}|$ 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.

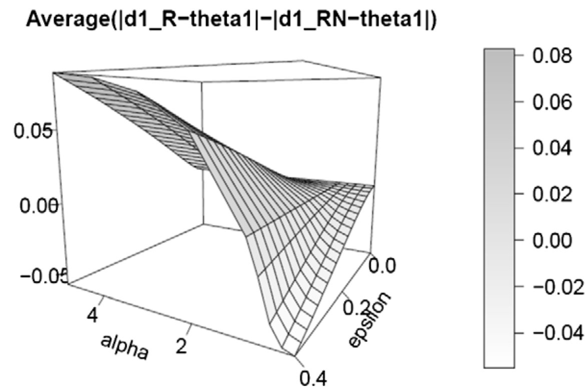


(b) Comparison of average distances between optimal risk-averse and risk-neutral decisions, $|d_1^{\mathrm{RA}} - d_2^{\mathrm{RA}}| - |d_1^{\mathrm{RN}} - d_2^{\mathrm{RN}}|$ for $\gamma = \frac{3}{4}$. Each point corresponds to the average over $(\nu_1, \nu_2) \in [-0.6, 0.6]^2$ with a grid of size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

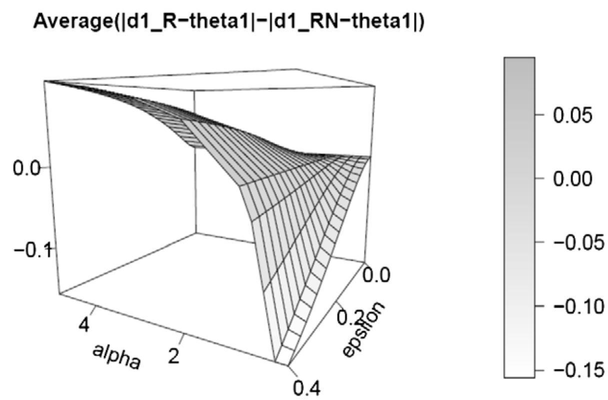
FIGURE S.4. The effect of risk aversion on coordination behavior in centralized coordination games.

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 $\epsilon \in [0, 0.4]$.[17] Figure S.5 shows the simulated average distances $D(\epsilon, \alpha) \equiv \mathrm{Mean}_{(\theta_1, d_2)}\{|d_1^R - \theta_1| - |d_1^{\mathrm{RN}} - \theta_1|\}$ 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

[17] 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, $|d_1^R - \theta_1| - |d_1^{\text{RN}} - \theta_1|$ 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, $|d_1^R - \theta_1| - |d_1^{\text{RN}} - \theta_1|$ 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 S.5. The effect of attitudes toward risk on the degree of adaptation in decentralized coordination games.

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.

Appendix J: Simulations for ambiguity preferences (centralization)

We now use simulations similar to those described in Appendices H and I 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:

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

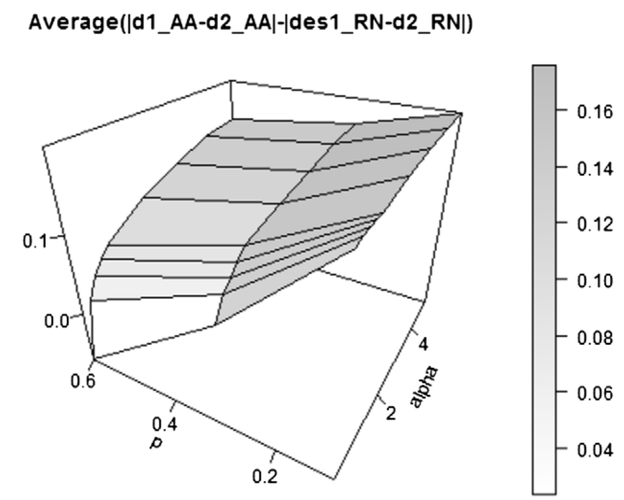
Here, μ indexes the principal's belief system, which specifies beliefs both about ν_1 and about ν_2.[18]

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.[19] 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.

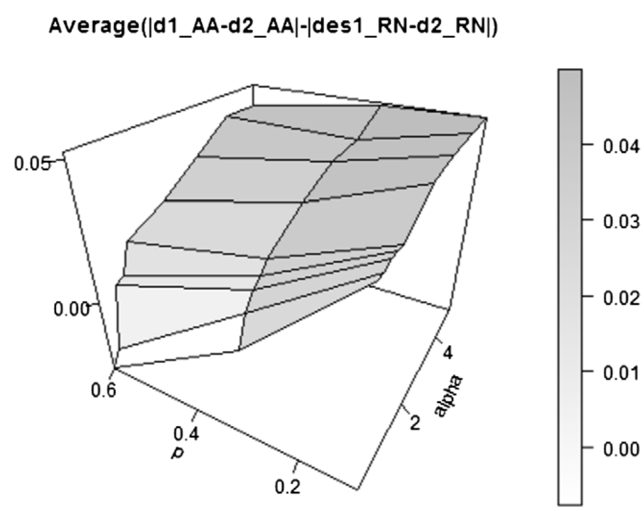
Our simulation results with different values of p and α are reported in Figure S.6 in the Appendix. These results show that introducing ambiguity-aversion amplifies the distortions caused by risk aversion considerably. Thus, even with risk neutrality, that is, $\alpha=1$, we obtain that the average difference in the distances, over our simulated values of p, is 0.121 for $\gamma=1/4$ and 0.028 for $\gamma=3/4$. Increasing the risk aversion coefficient to $\alpha=2$ increases the average difference in distance to 0.1388 for $\gamma=1/4$ and 0.036 for $\gamma=3/4$, thus tripling the average distances compared to an ambiguity neutral but risk averse agent 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 16% to 50% 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.

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

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



(a) Comparison of average distances between optimal maxmin and risk/ambiguity-neutral decisions, $|d_1^{\mathrm{AA}} - d_2^{\mathrm{AA}}| - |d_1^{\mathrm{RN}} - d_2^{\mathrm{RN}}|$ 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, $|d_1^{\mathrm{AA}} - d_2^{\mathrm{AA}}| - |d_1^{\mathrm{RN}} - d_2^{\mathrm{RN}}|$ 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 S.6. The effect of ambiguity-aversion on coordination behavior in centralized coordination games.

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Co-editor Rosa L. Matzkin handled this manuscript.

Manuscript received 23 December, 2016; final version accepted 30 September, 2018; available online 2 November, 2018.