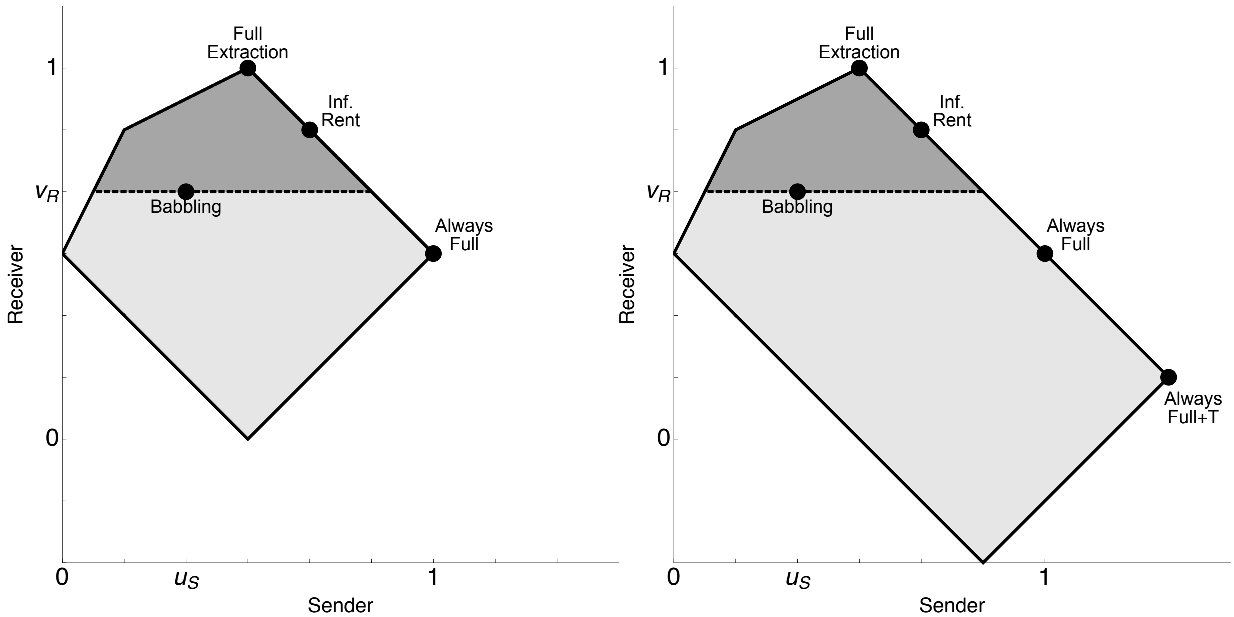
INFORMATION TRANSMISSION UNDER THE SHADOW OF THE FUTURE: AN EXPERIMENT

ONLINE APPENDICES A–C

ALISTAIR J. WILSON AND EMANUEL VESPA

APPENDIX A. ONLINE APPENDIX: ADDITIONAL FIGURES AND TABLES



(A) Partners (no transfer)   (B) Parners (with transfer)

FIGURE A1 . Feasible and IR Discounted-Average Payoffs: Partners vs. Distribution

Date: November, 2016.

TABLE A1. Discounted-average Payoffs

Treatment	N_{SG}	Partners					N_{SG}	Strangers				
Senders:		$(1-\delta)\cdot\hat{u}_1$	+	$\delta\cdot\hat{U}_{2+}$	=	$\hat{U}$		$(1-\delta)\hat{u}$	+	$\delta\cdot\hat{U}_{2+}$	=	$\hat{U}$
$m_1 =$ Invest $\vert\theta_1 =$ Bad	133	0.430	+	0.880	=	1.294	166	0.422	+	0.964	=	1.386
		(0.022)		(0.087)		(0.091)		(0.019)		(0.086)		(0.087)
$m_1 =$ Don't $\vert\theta_1 =$ Bad	97	0.111	+	1.137	=	1.242	58	0.134	+	0.668	=	0.802
		(0.019)		(0.128)		(0.126)		(0.025)		(0.112)		(0.115)
Receivers		$(1-\delta)\cdot\hat{v}_1$	+	$\delta\cdot\hat{V}_{2+}$	=	$\hat{V}$		$(1-\delta)\hat{v}$	+	$\delta\cdot\hat{V}_{2+}$	=	$\hat{V}$
$a_1 =$ Full $\vert m_1 =$ Invest	149	0.498	+	1.262	=	1.760	144	0.438	+	1.233	=	1.670
		(0.030)		(0.122)		(0.122)		(0.031)		(0.115)		(0.120)
$a_1 =$ Partial $\vert m_1 =$ Invest	206	0.500	+	1.489	=	1.990	243	0.500	+	1.388	=	1.888
		(–)		(0.110)		(0.110)		(–)		(0.090)		(0.090)
$a_1 =$ Invest $\vert m_1 =$ Don't	66	0.750	+	1.583	=	2.333	34	0.728	+	1.243	=	1.971
		(–)		(0.195)		(0.195)		(0.022)		(0.276)		(0.268)
$a_1 =$ Partial $\vert m_1 =$ Don't	27	0.500	+	1.269	=	1.769	23	0.500	+	1.239	=	1.809
		(–)		(0.278)		(0.278)		(–)		(0.266)		(0.115)

Note: Standard-errors are in parentheses and are derived from a bootstrap (of size 5,000) with supergame-level resampling across the supergames for each subsample.

TABLE A2. Coded Chat Data

Question	Coder 1	Coder 2	Agreement
"Who initiates the conversation? Enter 1 for Recommender, 2 for Decision-Maker"	1.39 (180)	1.39 (180)	1.39 (177)
We will call "a message" each time one party sends information to the other. How many messages does the Recommender send?	2.36 (180)	2.36 (180)	2.29 (171)
How many messages does the Decision-Maker send?	2.10 (180)	1.95 (180)	1.92 (180)
How many messages that the Recommender sends are related to discussing behavior in the game?	1.93 (180)	1.73 (180)	1.52 (129)
How many messages that the Decision-Maker send are related to discussing behavior in the game?	1.62 (180)	1.38 (180)	1.25 (129)
Does the chat mention Strategy X [the information rents strategy]?[a] Enter 1 for yes, 0 for no (go to XX).	0.74 (180)	0.77 (180)	0.77(175)
Which party first makes a reference to Strategy X? Enter 1 for Recommender, 2 for Decision-Maker.	1.49 (134)	1.47 (139)	1.47 (125)
Does the full discussion of Strategy X result in an exchange of messages or is simply proposed by one party? Enter 1 for exchange of messages, 2 for one party.	1.85 (134)	1.81 (139)	1.87 (118)
Who states that the Decision-Maker will pick Middle if the recommendation is Go Right? Enter 1 for Recommender, 2 for Decision- Maker, 3 for both.	1.68 (134)	1.70 (139)	1.67 (132)
Does the conversation at some point clearly state that there are punishments for not satisfying the agreement?	0.07 (134)	0.07 (139)	0.07 (134)
Who first makes a statement about punishments? Enter 1 for Recommender, 2 for Decision-Maker, 3 for both.	1.9 (10)	1.9 (10)	1.9 (10)
The punishments that subjects discuss correspond to those of Strategy X? Enter 1 if yes, 0 if no.	0.82 (11)	1.0 (10)	1.0 (9)
After subjects discuss Strategy X, is there a proposal for not using Strategy X?	0.11 (134)	0.7 (10)	0.0 (3)
Does the chat mention Strategy Y [full extraction]? Enter 1 for yes, 0 for no (go to YY).	0.11 (180)	0.07 (180)	0.07(169)
Which party first makes a reference to Strategy Y? Enter 1 for Recommender, 2 for Decision-Maker.	1.60 (20)	1.54 (13)	1.60 (10)
Does the full discussion of Strategy Y result of an exchange of messages or is simply proposed by one party? Enter 1 for exchange of messages, 2 for one party.	1.70 (20)	2.00 (13)	2.00 (9)
Does the conversation at some point clearly state that there are punishments for not satisfying the agreement?	0.00 (19)	0.00 (13)	0.00 (10)
Who first makes a statement about punishments? Enter 1 for Recommender, 2 for Decision-Maker, 3 for both.			
Do the punishments subjects discuss correspond to those of Strategy Y? Enter 1 if yes, 0 if no.			
After subjects discuss Strategy Y, is there a proposal for not using Strategy Y?	0.10 (19)	(0)	(0)
Is there a discussion of a Strategy that does not correspond to either Strategy X or Strategy Y? Enter 1 if yes, 0 if no.	0.22 (180)	0.18 (180)	0.15 (153)
Is there a explicit reference to truthfulness or honesty in the chat?	0.46 (179)	0.38 (180)	0.41 (158)
If there is an explicit reference to truthfullness or honesty, who makes it? Enter 1 for Recommender, 2 for Decision-Maker, 3 for both.	1.64 (80)	1.61 (71)	1.56 (54)

[a]Defined for coders as: The Recommender tells the truth. The Decision-Maker picks Left when the message is Go Left and Middle when the recommendation is Go Right. If in any period either the Recommender or the Decision-Maker does something different, then from the next period onwards the Decision- Maker will always select middle.

Table A3. Tobit Regression on Supergame Efficiency

Variable	Coeff.		Std. Err	Marginal Effect		Std. Err
Mention Information Rents strategy	1.903	***	0.637	0.505	**	0.204
Mention Full Extraction strategy	0.206		0.683	0.067		0.219
Mention Other Strategy	0.790		0.624	0.256		0.200
Supergame Number	0.0127		0.084	0.002		0.027
Constant	0.705		0.544	0.404	**	0.179

Note: The Tobit regression examines the subsample of 192 chat supergames for 118 supergames with: i) One or more rounds in the good state, which eliminates 42 supergames); and ii) perfect agreement between the two chat coders, which eliminates 43 supergames, 11 overlapping with condition (i). The Tobit controls for censoring at an efficiency level of 100 percent, as 102 of the 118 supergames are perfectly efficient. Marginal effects are the change in probability (base probability for the constant) of achieving a perfectly efficient supergame (the censored region for the Tobit) as each variable shifts from 0 to 1. Standard errors for the marginal effects calculated using the delta method.

Appendix B. Online Appendix: Analysis at the aggregate level

In this section we provide statistical support for the statements in Sections 3–5. We now describe the approach that we follow to compare across treatments. In the case of senders, the vast majority of messages are to Invest when the state is good, so the informative comparisons take place when the state is bad, so we therefore focus our analysis on these cases. The dependent variable in the analysis is a dummy that takes value 1 if the subject sent the message Invest and 0 otherwise. On the right-hand-side we have a treatment dummy (to be specified in each comparison) and a constant.

For receivers, we conduct two separate sets of regressions. First, we consider the case when the message is Invest. When such message is received, the informative comparison is to evaluate if the receiver decides to fully invest or not. Hence, we define the dependent variable in this case as 1 if the receiver fully invests and 0 otherwise. Second, consider the case when the message is *Don't Invest*. In this case, we want to evaluate if the receiver selects *Partial* or not. Hence, our dependent variable in this case is a dummy variable that takes value 1 if the receiver's action is *Partial* and 0 otherwise. In each case we report the estimates on the right-hand-side decision using a random-effects linear probability model.[1]

Table B4 reports the results for a comparison of the *Partners* and the *Strangers* treatment, with the treatment dummy (*Parters*) taking value 1 (0) if the observation comes from the *Partners* (*Strangers*) treatment. In each case we present the output including all supergames (All S) and also constrained to the last eight supergames ($S > 12$). The findings are in line with the test of proportion we report in the text: there are basically no statistical differences at the aggregate level between the Partners and the Strangers treatment either with respect to the behavior of Senders or Receivers. In the next appendix section we show, however, that there are small differences across these two treatments when we condition on past play.

Table B5 presents the comparison between the *Chat* and *Partners* treatments, with the treatment dummy (*Chat*) taking value 1 (0) if the observation comes from the *Chat* (*Partners*) treatment. The table presents the output for supergames prior to the introduction of pre-play communication ($S \leq 12$) and supergames with pre-play communication ($S > 12$). There is no statistical differences across treatments prior to the introduction of pre-play communication, but there are large and statistically significant treatment effects once chat is introduced in all cases. For senders, in the last eight supergames, we find a negative treatment effect, which means that subjects are less likely to dishonestly send the message *Inves*t in the bad state. Meanwhile, we find that receivers are much more likely to follow the sender's recommendation when the message is *Invest*. In this case,

[1]We decided to report a linear probability model for ease of presentation. The results are qualitatively similar if we estimate a random effects probit model for the senders or an random effects ordered probit for receivers (given that receivers are deciding among three ordered options).

subjects in the Chat treatment select *Full* significantly more often than in *Partners*. On the other hand, when the message is *Don't Invest*, receiver subjects in the *Chat* treatment are much more likely to select *Partial* investment, consistent with the information-rents strategy.

Table B6 displays the output for the comparison between the *Revelation* and *Partners* treatments, with the treatment dummy (*Revelation*) taking value 1 (0) if the observation comes from the *Revelation* (*Partners*) treatment. We present results for all supergames and for the last eight supergames in each case. We basically find that there is no significant treatment effect relative to *Partners*. Moreover, the estimates for the treatment dummy are quantitatively small .

Finally, Table B7 shows the output for the comparison between the *Distribution* treatment (with the treatment dummy *Distribution* taking value 1) and the *Partner*s treatment (with the treatment dummy taking value 0). In this case we do find differences in behavior for senders and receivers. In the case of senders we find that subjects are more likely to tell the truth in the *Distribution* treatment. The increase of truth-telling is between 20 and 30 percentage points. We find a significant effect for receivers when the message is invest if we focus on all periods. The treatment effect involves an increase between 11 and 21 percentage points. Finally, in all cases we find a difference in choices when the message is *Don't Invest*. In this case, subjects are more less likely to choose *Partial* in the *Distribution* treatment. The reason for this is that receivers are choosing *None* much more often (but are instead opting to make an explicit transfer).

	Senders				Receivers							
	$\theta =$ Bad				$m =$ Invest				$m =$ Don't Invest			
	All S		$S > 12$		All S		$S > 12$		All S		$S > 12$	
	$t = 1$	All t	$t = 1$	All t	$t = 1$	All t	$t = 1$	All t	$t = 1$	All t	$t = 1$	All t
Partners	-0.167	-0.110	-0.219*	-0.087	0.054	0.043	0.097	0.047	-0.145	-0.066	-0.033	-0.084
	(0.103)	(0.075)	(0.121)	(0.078)	(0.103)	(0.072)	(0.115)	(0.071)	(0.120)	(0.103)	(0.174)	(0.126)
Constant	0.738***	0.788***	0.811***	0.829***	0.357***	0.284***	0.273***	0.217***	0.407***	0.380***	0.341***	0.416***
	(0.073)	(0.053)	(0.085)	(0.055)	(0.073)	(0.051)	(0.081)	(0.050)	(0.091)	(0.074)	(0.142)	(0.093)

TABLE B4. Linear Probability Models: Partners vs. Strangers Treatment Effects

Notes: Dependent variables are dummy variables. For Senders: takes value 1 if $m =$ Invest. For Receivers: i) if $m =$ Invest, it takes value 1 if $a =$ Full and 0 otherwise; ii) if $m =$ Don't, takes value 1 if $a =$ Partial and 0 otherwise. Partners is a dummy variable that takes value 1 if the observation is from the Partners treatment and 0 if it is from the Strangers treatment. Standard-Errors between parentheses. (*), (**), (***), denote significant at the 10, 5 and 1 percent levels, respectively. In each case we estimate a linear probability model taking into account the panel structure (random effects). Other legends: $t = 1$ regressions only use the first period of each supergame; $S > 12$ regressions use only the last 8 supergames of the session.

	Senders				**Receivers**							
	$\theta =$ Bad				$m =$ Invest				$m =$ Don't Invest			
	$S \leq 12$		$S > 12$		$S \leq 12$		$S > 12$		$S \leq 12$		$S > 12$	
	$t = 1$	All t	$t = 1$	All t	$t = 1$	All t	$t = 1$	All t	$t = 1$	All t	$t = 1$	All t
Chat	0.058	0.020	-0.438***	-0.555***	0.028	0.027	0.501***	0.574***	0.062	-0.018	0.403***	0.378***
	(0.097)	(0.072)	(0.112)	(0.074)	(0.108)	(0.072)	(0.100)	(0.070)	(0.121)	(0.100)	(0.113)	(0.099)
Constant	0.561***	0.619***	0.592***	0.742***	0.443***	0.384***	0.370***	0.265***	0.223***	0.303***	0.322***	0.338***
	(0.069)	(0.051)	(0.080)	(0.053)	(0.077)	(0.051)	(0.071)	(0.050)	(0.086)	(0.071)	(0.087)	(0.075)

TABLE B5. Linear Probability Models: Chat vs. Partners Treatment Effects

Notes: Dependent variables are dummy variables. For Senders: takes value 1 if $m =$ Invest. For Receivers: i) if $m =$ Invest, it takes value 1 if $a =$ Full and 0 otherwise; ii) if $m =$ Don't, takes value 1 if $a =$ Partial and 0 otherwise. Chat is a dummy variable that takes value 1 if the observation is from the Chat treatment and 0 if it is from the Partners treatment. Standard-Errors between parentheses. (*), (**), (***), denote significant at the 10, 5 and 1 percent levels, respectively. In each case we estimate a linear probability model taking into account the panel structure (random effects). Other legends: $t = 1$ regressions only use the first period of each supergame; $S > 12$ regressions use only the last 8 supergames of the session.

	Senders				Receivers							
	$\theta =$ Bad				$m =$ Invest				$m =$ Don't Invest			
	All S		$S > 12$		All S		$S > 12$		All S		$S > 12$	
	$t = 1$	All t	$t = 1$	All t	$t = 1$	All t	$t = 1$	All t	$t = 1$	All t	$t = 1$	All t
Revelation	0.017	-0.036	-0.019	-0.093	-0.018	0.026	0.013	0.062	-0.145	-0.066	-0.033	-0.084
	(0.113)	(0.084)	(0.138)	(0.093)	(0.103)	(0.066)	(0.123)	(0.074)	(0.120)	(0.103)	(0.174)	(0.126)
Constant	0.571***	0.677***	0.592***	0.742***	0.411***	0.326***	0.369***	0.264***	0.407***	0.380***	0.341***	0.416***
	(0.080)	(0.059)	(0.098)	(0.065)	(0.072)	(0.047)	(0.086)	(0.052)	(0.091)	(0.074)	(0.142)	(0.093)

TABLE B6. Linear Probability Models: Revelation Device vs. Partners Treatment Effects

Notes: Dependent variables are dummy variables. For Senders: takes value 1 if $m =$ Invest. For Receivers: i) if $m =$ Invest, it takes value 1 if $a =$ Full and 0 otherwise; ii) if $m =$ Don't, takes value 1 if $a =$ Partial and 0 otherwise. *Revelation Device* is a dummy variable that takes value 1 if the observation is from the Revelation treatment and 0 if it is from the Partners treatment. Standard-Errors between parentheses. (*), (**), (***), denote significant at the 10, 5 and 1 percent levels, respectively. In each case we estimate a linear probability model taking into account the panel structure (random effects). Other legends: $t = 1$ regressions only use the first period of each supergame; $S > 12$ regressions use only the last 8 supergames of the session.

	Senders				Receivers							
	θ = Bad				m = Invest				m = Don't Invest			
	All S		$S > 12$		All S		$S > 12$		All S		$S > 12$	
	$t = 1$	All t	$t = 1$	All t	$t = 1$	All t	$t = 1$	All t	$t = 1$	All t	$t = 1$	All t
Distribution	-0.214**	-0.205**	-0.254*	-0.284***	0.129	0.167**	0.114	0.214**	-0.168**	-0.186**	-0.230**	-0.213**
	(0.109)	(0.080)	(0.135)	(0.089)	(0.112)	(0.079)	(0.130)	(0.091)	(0.082)	(0.078)	(0.100)	(0.091)
Constant	0.571***	0.678***	0.592***	0.742***	0.411***	0.326***	0.369***	0.265***	0.264***	0.314***	0.316***	0.334***
	(0.077)	(0.057)	(0.096)	(0.065)	(0.079)	(0.047)	(0.091)	(0.064)	(0.060)	(0.056)	(0.074)	(0.066)

TABLE B7. Linear Probability Models: Distribution vs. Partners Treatment Effects

Notes: Dependent variables are dummy variables. For Senders: takes value 1 if m = Invest. For Receivers: i) if m = Invest, it takes value 1 if a = Full and 0 otherwise; ii) if m = Don't, takes value 1 if a = Partial and 0 otherwise. *Distribution Device* is a dummy variable that takes value 1 if the observation is from the Distribution treatment and 0 if it is from the Partners treatment. Standard-Errors between parentheses. (*), (**), (***), denote significant at the 10, 5 and 1 percent levels, respectively. In each case we estimate a linear probability model taking into account the panel structure (random effects). Other legends: $t = 1$ regressions only use the first period of each supergame; $S > 12$ regressions use only the last 8 supergames of the session.

APPENDIX C. ONLINE APPENDIX: HISTORY DEPENDENCE

Analysis at the aggregate level. Though the overall data indicates a modal response that exactly reflects the babbling outcome, we now show that subjects in our *Partners* treatment do react to history within the supergame. Table C8 presents aggregate evidence that subjects respond to history in the *Partners* treatment but not in *Strangers*. To define the dependent variables for senders and receivers we follow a similar approach as described in Appendix B: For senders we focus on cases when the state is bad and the dependent variable equals one if the subject recommends *Invest*. For receivers we distinguish based on the current message. If the message is *Invest*, the dependent variable takes value 1 if the subject chooses *Full* investment and 0 otherwise. If the message is *Don't Invest*, the dependent variable takes value 1 if the subject chooses *Partial* and 0 otherwise. We present results for all supergames and for the the last eight. In addition, in each case we distinguish between a sample that includes only the second period (after there is a single period of previous history, we label these regressions as "$t = 2$") and all periods after the first ("$t \geq 2$").

On the right-hand side we include three control variables. A treatment dummy that takes value 1 if the observation is from *Partners*. An Information Rents feedback dummy: i) for senders it takes value 1 if in the previous period the message was *Invest* and the receiver selected *Full*, or if the message was *Don't Invest* and the receiver selected *Partial*; ii) for receivers it takes value 1 if the sender's message was truthful in the previous period. In other words the dummy captures cases where the outcome last period was 'positive', and we would expect a reaction to past play after such positive events. Finally, we also include the interaction between the Information Rents feedback and *Partners* treatment dummy.

The main finding in the table is that the interaction dummy is always significant for senders and it is significant for receivers after Invest messages. This indicates, that senders are significantly more likely to respond by telling the truth in the current period if the feedback last period was positive and they are participating in *Partners*. Meanwhile there is no effect on truth-telling after positive feedback to senders in the *Strangers* treatment.

In the case of receivers, we document no significant effect of past play on choices in a round with a *Don't Invest* message, receiver subjects in both *Strangers* and *Partners* react similarly. However, there is a treatment effect for receivers when the message is *Invest*. In this case, subjects are more likely to follow the advice in period t if the sender told the truth in the last period. The effect is significantly larger in the *Partners* treatment.

Analysis at the Individual Level.

SFEM. To examine if choices at the individual level are consistent with the findings at the aggregate level we use the *Strategy Frequency Estimation Method* (SFEM, see Dal Bó and Fréchette,

	Senders				Receivers							
	$\theta =$ Bad				$m =$ Invest				$m =$ Don't Invest			
	All S		$S > 12$		All S		$S > 12$		All S		$S > 12$	
	$t = 2$	$t \geq 2$	$t = 2$	$t \geq 2$	$t = 2$	$t \geq 2$	$t = 2$	$t \geq 2$	$t = 2$	$t \geq 2$	$t = 2$	$t \geq 2$
Partners	-0.095	-0.058	0.013	0.008	0.026	-0.030	-0.026	-0.062	-0.116	-0.022	-0.111	0.006
	(0.097)	(0.072)	(0.105)	(0.070)	(0.090)	(0.064)	(0.104)	(0.067)	(0.205)	(0.123)	(0.396)	(0.171)
Info. Rent Feedback	-0.001	-0.025	0.042	0.018	0.192***	0.079***	0.165**	0.049	-0.126	-0.114*	-0.143	-0.033
	(0.058)	(0.058)	(0.099)	(0.045)	(0.049)	(0.023)	(0.067)	(0.031)	(0.124)	(0.066)	(0.157)	(0.098)
Partners $\times$ Inf.Rent	-0.168**	-0.135***	-0.311**	-0.225***	0.085***	0.108***	0.190**	0.166***	0.055	0.010	0.004	-0.098
	(0.082)	(0.041)	(0.134)	(0.063)	(0.071)	(0.033)	(0.096)	(0.044)	(0.192)	(0.090)	(0.418)	(0.150)
Constant	0.785***	0.816***	0.778***	0.830***	0.152***	0.212***	0.101	0.168***	0.527***	0.453***	0.611***	0.454***
	(0.068)	(0.051)	(0.073)	(0.050)	(0.063)	(0.045)	(0.072)	(0.047)	(0.130)	(0.086)	(0.167)	(0.114)

TABLE C8. History Dependence: Partners vs. Strangers Treatment Effects

Notes: Dependent variables are dummy variables. For Senders: takes value 1 if $m =$ Invest. For Receivers: i) if $m =$ Invest, it takes value 1 if $a =$ Full and 0 otherwise; ii) if $m =$ Don't, takes value 1 if $a =$ Partial and 0 otherwise. Partners is a dummy variable that takes value 1 if the observation is from the Partners treatment and 0 if it is from the Strangers treatment. Positive Feedback takes value 1 if a) Senders: The Receiver in $t = 1$ selected i) Full and the message was Invest, or ii) Partial and the message was Don't; b) Receivers: The Sender told the truth in $t = 1$. Standard-Errors between parentheses. (*), (**), (***), denote significant at the 10, 5 and 1 percent levels, respectively. In each case we estimate a linear probability model taking into account the panel structure (random effects). Other legends: i) $t = 2$, the data set is constrained to the second period of each supergame, ii) $t \geq 2$ the data set is constrained to all periods after the first; iii) $S > 12$ regressions use only the last 8 supergames of the session.

2011).[2] For a given set of strategies, the SFEM evaluates which of these strategies subjects' choices are consistent with. Specifically, the procedure uses choices at the individual level to recover ϕ_k, the frequency attributed to strategy k in the data. To illustrate how the SFEM works, consider a finite set of strategies $\mathcal{K}$ that subjects may follow. Let $d^i_{gp}(\mathbf{h})$ be the choice of subject i and $k^i_{gp}(\mathbf{h})$ the decision prescribed for that subject by strategy $k \in \Phi$ in period p of supergame g for a given history $\mathbf{h}$. Strategy k is a perfect fit for period p if $d^i_{gp}(\mathbf{h}) = k^i_{gp}(\mathbf{h})$. The procedure models the probability that the choice (d) corresponds to the prescription of strategy k as:

$$(1) \qquad \Pr\left(d^i_{gp}(\mathbf{h}) = k^i_{gp}(\mathbf{h})\right) = \frac{1}{1 + (|\mathcal{A}| - 1)\exp\left(\frac{-1}{\gamma}\right)} = \beta.$$

In (1), $|A|$ represents the number of available actions (2 in the case of senders, 3 in the case of receivers) and $\gamma > 0$ is a parameter to be estimated. One interpretation of equation (1) is that subjects can make mental errors in the implementation of a strategy, β captures the probability that the subject does not make such error. To provide some intuition it is useful to consider the limit values that β can take. On the one hand, as $\gamma \to 0$, $\beta \to 1$ and the fit is perfect. On the other hand, as $\gamma \to \infty$, $\beta \to \frac{1}{|\mathcal{A}|}$. In this case, the estimate of γ is so high that the prediction of the model is no better than a random draw.[3]

With the specification for the mental error in (1), the procedure uses maximum likelihood to estimate the frequency of strategy k in the data (ϕ_k) and parameter γ. Let y^i_{gp} be an indicator that takes value one if the subject's choice matches the decision prescribed by the strategy. Since Equation (1) specifies the probability that a choice in a specific period corresponds to strategy k, the likelihood of observing strategy k for subject i is given by:

$$(2) \qquad p_i(k) = \prod_g \prod_p \left(\frac{1}{1 + (|\mathcal{A}| - 1)\exp\left(\frac{-1}{\gamma}\right)}\right)^{y^i_{gp}} \left(\frac{1}{1 + (|\mathcal{A}| - 1)\exp\left(\frac{1}{\gamma}\right)}\right)^{1-y^i_{gp}}.$$

Aggregating over subjects we get: $\sum_i \ln\left(\sum_k \phi_k p_i(k)\right)$. The procedure maximizes the likelihood function to obtain estimates for γ and the strategy frequencies ϕ_k.[4]

An example may serve to clarify some aspects of the approach. Consider the case of senders with two available actions (***Invest*** and ***Don't Invest***), and where only two strategies are included in set $\mathcal{K}$, to always say $Invest$ (All I) and to always say $Don't\ Invest$ (All D). The fit will be good (high

[2] We describe the procedure next but the reader is referred to Fudenberg et al. (2010) and Embrey et al. (2013) for further details.

[3] For example, with two choices ($|A| = 2$) if $\beta = 0.5$ the estimates are no better than a simple toss of a coin to determine the choice.

[4] Notice that since $\sum\limits_k \phi_k = 1$, the procedure will provides $|\mathcal{K}| - 1$ estimates and the estimate for the $|\mathcal{K}|$-th strategy is computed by difference.

β) if the population is composed of subjects who either almost-always select $Invest$ or almost-always select $Don't\ Invest$. The estimated frequency $\phi_{\text{All Invest}}$ would be the maximum-likelihood estimate of the proportion of subjects who almost always select $Invest$.[5] If a large proportion of senders shifts between $Invest$ and $Don't\ Invest$ within the supergame, neither strategy would accommodate their choices well, which the procedure will measure with a low estimate for β.

Included Strategies and the One-Period-Ahead Strategy Method. Clearly, the estimated frequencies depend on the set of included strategies. However, our goal with the estimation is not in identifying all strategies that subjects may be using but rather to check if for a small set of strategies that are consistent with aggregate behavior, the overall fit is good (high β). When the fit is good, the data can be rationalized with the included strategies and we will evaluate the strategies with higher frequencies as corresponding to aggregate behavior. We find positive answers in both cases in our estimates: the overall fit is good with just a few strategies, and the estimated frequencies are consistent with the findings at the aggregate level.

Table C9 presents all strategies considered, indicating if they refer to the Sender or Receiver. For Senders we include three strategies that do not condition on past play (*Truth*, *Always Inves*t, *Always Don't*) and two strategies that condition honesty on past play triggers (*Information Rent*, *Full Extraction*). For Receivers, we include five strategies that do not condition on past play (*Follow Message*, *Always Full*, *Always Partial*, *Always None*) and two that do (*Information Rent*, *Full Extraction*) which we define with babbling triggers.

Notice that, in principle, the identification of strategies that condition on past play is only possible if punishments path are reached. To see why, consider a sender-receiver pair that are using the complementary *Information Rent* strategies. If they never deviate from full revelation, the observed part of the strategy for senders is observational equivalent to a strategy pair that does not condition on past play (*Truth*, *Follow Message*). More generally, the problem is that strategies are infinite-dimensional objects (prescribing an action at every possible decision node), but in the laboratory we only observe part of the path.

At the design stage, we anticipated that it may be challenging to identify strategies and to procure more data we used a one-period-ahead strategy method (Vespa, 2016). In the last five supergames of the *Partners* and *Strangers* treatment we asked subjects in an incentivize compatible manner to provide information about counterfactual choices that were not eventually implemented.[6] The

[5]The procedure would estimate two parameters in this case. The first parameter is $\phi_{\text{All } I}$, that would capture the frequency of All I. (The frequency of All D would be computed as $1 - \phi_{\text{All } I}$.) The second parameter is the estimate of γ. Following Equation (1) there is a one-to-one mapping between γ and β, so we will refer to the estimate of γ directly as an estimate of β.

[6]We did not implement the one-period-ahead strategy method in the *Chat*, *Revelation* or *Distribution* treatments. In the *Chat* treatment we are already introducing a modification in the later part of the session (pre-play communication). The other two manipulations involve a more complex environment than the *Partners* or the *Strangers* treatment.

Agent	Abbreviation	Description	Comments for the Distribution treatment
Sender	Truth	$Invest$ if $\theta = Good$, $Don't$ if $\theta = Bad$.	
	Always Invest	$Invest$ for $\theta = \{Good, Bad\}$	
	Always Don't	$Don't\ Invest$ for $\theta = \{Good, Bad\}$	
	Information Rent	Truth if $t = 1$ or if outcome was $Full$ when $m = Invest$ and $Partial$ when $m = Don't$ in $t-1$. Always Invest otherwise.	Also Truth if previous outcome was $None$ when $m = Don't$ and there was a transfer
	Full Extraction	Truth if $t = 1$ or if outcome was $Full$ when $m = Invest$ and $None$ when $m = Don't$ in $t-1$. Always Invest otherwise.	We require that there is no transfer if the receiver chose $None$ when $m = Don't$.
Receiver	Follow	$Full$ if $m = Invest$, $None$ if $m = Don't$	
	Always Partial	$Partial$ if $m = Invest$, $Partial$ if $m = Don't$	
	Always Full	$Full$ if $m = Invest$, $Full$ if $m = Don't$	
	Always None	$None$ if $m = Invest$, $None$ if $m = Don't$	
	Partial/None	$Partial$ if $m = Invest$, $None$ if $m = Don't$	
	Information Rent	$Full$ if $m = Invest$ and$Partial$ if $m = Don't$ if $t = 1$ or if $\theta = Good$ when $m = Invest$ and $\theta = Bad$ when $m = Don't$ in $t-1$. Partial/None otherwise.	$Partial$ also includes $None$ plus transfer $None$ includes only $None$ plus no transfer
	Full Extraction	$Full$ if $m = Invest$ and$None$ if $m = Don't$ if $t = 1$ or if $\theta = Good$ when $m = Invest$ and $\theta = Bad$ when $m = Don't$ in $t-1$. Partial/None otherwise.	$Partial$ also includes $None$ plus transfer $None$ includes only $None$ plus no transfer

TABLE C9. Strategies included in the Estimation supergame starts in period one just as any other supergame: senders observe θ and send a message m, then receivers observe m and select an action a. The feedback stage is modified: senders are not informed of the receiver's choice of a and receivers are not informed of the actual state of the world θ. The supergame moves on to period $t \geq 2$. Senders observe θ_t but are asked to make three choices: select a message they'd like to send for each possible receiver choice in the previous period. That is, they select $m_t(a_{t-1})$, a message to send for each possible choice a_{t-1} that the receiver could have made in the previous period. When they submit their three choices senders do not know the actual a_{t-1}, so all choices are incentivized. The interface sends then sends the receiver the message corresponding to the actual action a_{t-1} selected last period.

For the receiver in period $t \geq 2$, we show them the current message m_t, but ask them to make action choices contingent on the two possible true states last round. That is, receivers submit $a_t(\theta_{t-1})$. Since they do not know the realized value of θ_{t-1} yet, both choices are incentivized. In the feedback stage for periods $t \geq 2$, senders are informed of the actual a_{t-1} and receivers are informed of the actual θ_{t-1}, but not of the corresponding values for the current period. Periods from the second onwards therefore proceed in an identical manner.

The one-period-ahead strategy method allows us to partially observe choices that are off path. This extra information can aid in distinguishing between strategies. For example, we are able to distinguish between senders using the strategy *Truth* and another succeeding with the history-dependent strategy *Information Rent*, because we get to observe counterfactual choices given receiver deviations. The extra information is particularly useful when there is a lot of heterogeneity in the data as it helps understand which strategies best rationalize subjects' choices.

However, the aggregate analysis for the *Strangers* and *Partners* treatments does not show large levels of heterogeneity: most choices are consistent with history-independent babbling. This suggests that information from the unimplemented parts of the strategy is not crucial for identification here. Indeed we find that this is the case. For the purpose of comparing with and without the one-period-ahead strategy method we would ideally present estimates using the first 15 supergames and the last 5. However, to make the estimates comparable to the Chat treatment, where pre-play communication is introduced after 12 supergames, we show estimates using data from the first twelve ($S \leq 12$) and last eight supergames ($S > 12$).[7]

Outcomes: Senders. Table C10 presents the output for the case of senders. Notice first that the goodness of fit -as measured by β- is in all cases far from $\frac{1}{2}$, the random-choice benchmark.

We start by describing the frequency output for the *Partners* treatment that will serve as a baseline to compare other treatments against. Two strategies show statistically significant coefficients and

[7]There are no qualitative differences between estimates using the last five or the last eight supergames (first 12 or first 15 supergames) in the *Strangers* and *Partners* treatments.

concentrate almost all the mass: *Always Invest* and *Information Rent*. That the frequency of *Always Invest* is close to 60 percent towards the end of the session is consistent with modal behavior being coordinated at the babbling equilibrium. There is, however, between 20-25 percent of the estimated mass attributed to the *Information Rent* strategy which truthfully reveals until the receiver chooses either *None* in response to *Don't Invest* (no rent paid) or chooses *Partial* after an *Invest* message. After this trigger the strategy becomes identical to *Always Invest*.

The estimated mass attributed to the Information-Rent trigger suggests that there is a proportion of senders who start the supergames trying to coordinate on more-efficient outcomes. However, were these of senders trying to implement the Information Rents path successful, we would observe treatment effects at the aggregate level in Table B4. Instead, the evidence suggest that most subjects who try to implement the *Information Rent* outcome path do not succeed for long as they are not matched with receivers who follow suit.

The main difference between the *Partners* and *Strangers* treatments is that in the latter babbling captures between 75-80 percent, approximately 20 percentage points more than in the former. There is almost no mass attributable to strategies that condition the sender's response on past play, suggesting that (consistent with theory) history does not play a role in this treatment. This analysis suggests that as a measure of subject's intentions as senders, focusing on data at the aggregate level may be misleading. There does appear to be a proportion of senders in *Partners* capable of sustaining efficient play if rewarded by a rent.

While the SFEM estimates for the first 12 supergames of the *Chat* treatment is clearly in line with the *Partners* estimates, there is a sharp change in the last eight supergames. About a third of the mass corresponds to the Information-Rent strategy and close to 60 percent to Truth-telling. Note that in the *Chat* treatment we do not have implement a one-period-ahead strategy method, which means that we cannot know if subjects who are selecting *Truth* would punish if there were deviations. If we assume that these subjects would combine the estimated from *Truth* and the *Information Rent* strategy, then the total proportion of subjects using truthful strategies is at approximately 90 percent.

The output for the *Revelation* treatment is similar to *Partners*. First, *Always Invest* is still the modal strategy with approximately 60 percent of the estimated mass. Second, outcomes are again partially consistent with some sender attempting to reveal information. Here we find that subjects are more-likely to respond truthfully (in a history independent manner). Note that in this treatment, truth-telling is done in an ex ante manner. While there does seem to be a growing rate of truth-telling within the Revelation sessions, the modal behavior is still mostly consistent with babbling.

In the *Distribution* treatment the highest estimated frequency corresponds to the *Information Rent* strategy. However, the second-most-popular strategy, capturing about a third of the data, is *Always Invest*.

Finally, notice that the estimated mass for the strategies *Always Don't* and *Full Extraction* are almost always very small and never significant, across all treatments.

Outcomes: Receivers. Table C11 shows the SFEM output for receivers. In the case of receivers subjects are choosing between three possible actions, which means that the random choice benchmark for goodness of fit is $\frac{1}{3}$. In all cases the estimate of β is high and far from such value.

In the *Partners* and *Strangers* treatment we find that the vast majority of choices are consistent with babbling. Adding *Always Partial* and *Partial/None* we capture between 70-75 percent of the mass in both treatments. In the Partners treatment the history-dependent strategy with largest mass is *Full Extraction*, which uses a babbling trigger to support full extraction. Though capable of efficient choices after an *Invest* message, this strategy chooses *None* after *Don't Invest.* That this history-dependent strategy has the largest mass suggests that those receivers coordinating on efficient play are not paying for information. The history-dependent behavior in the *Partner*s treatment is therefore consistent with senders who require an information rent, and receivers who do not pay it.

The SFEM estimates from the *Chat* treatment are consistent with the *Partners* treatment for the first 12 supergames. Again, there is a substantial change in behavior once pre-play communication is introduced. The frequency of the *Information Rent* strategy at 90 percent is consistent with the corresponding behavior documented for senders (where the chats provide for the correlation in strategies).

Behavior of receivers in the *Revelation* treatment is similar to the *Partners* treatment. The majority of choices are consistent with babbling and where there is evidence of history-dependent behavior, most subjects do not seem to compensate senders for information. In contrast to *Revelation* (although lower than the levels estimated for *Chat*) modal behavior in the *Distribution* treatment is consistent with the *Information Ren*t strategy being selected by receivers. Though there is still substantial heterogeneity, and the rates do decrease across the session, when paying for information is possible with an explicit transfer there is a significant portion of receivers who pay the rent.

Finally, notice that strategies such as *Always Full* and *Always None* receive very little mass and are never statistically significant.

Table C10. SFEM Output: Senders

Strategies	Partners		Strangers		Chat		Revelation		Distribution	
	$S \leq 12$	$S > 12$	$S \leq 12$	$S > 12$	$S \leq 12$	$S > 12$	$S \leq 12$	$S > 12$	$S \leq 12$	$S > 12$
Truth	0.218	0.087	0.046	0.082	0.078	0.577***	0.152	0.251*	0.069	0.172
	(0.140)	(0.096)	(0.058)	(0.050)	(0.051)	(0.134)	(0.093)	(0.131)	(0.108)	(0.121)
Always Invest	0.561***	0.573***	0.758***	0.826***	0.650***	0.047	0.609***	0.622***	0.330***	0.346***
	(0.157)	(0.101)	(0.110)	(0.143)	(0.126)	(0.068)	(0.103)	(0.149)	(0.109)	(0.125)
Always Don't	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.032)	(0.000)
Information Rent	0.221**	0.237**	0.069	0.000	0.272**	0.331**	0.149*	0.061	0.601***	0.483***
	(0.089)	(0.093)	(0.075)	(0.011)	(0.107)	(0.132)	(0.086)	(0.093)	(0.116)	(0.112)
Full Extraction	0.000	0.103	0.127	0.092	0.000	0.044	0.091	0.066	0.000	0.000
γ	0.524***	0.434***	0.384***	0.459***	0.587***	0.396***	0.506***	0.423***	0.500***	0.407***
	(0.051)	(0.061)	(0.076)	(0.075)	(0.069)	(0.040)	(0.048)	(0.045)	(0.061)	(0.038)
β	0.871	0.909	0.931	0.898	0.846	0.926	0.878	0.914	0.881	0.921

Note: Bootstrapped standard errors in parentheses. Level of Significance: ***-1 percent; **-5percent; *-10 percent.

TABLE C11. SFEM Output: Receivers

Strategies	**Partners**		**Strangers**		**Chat**		**Revelation**		**Distribution**	
	$S \leq 12$	$S > 12$	$S \leq 12$	$S > 12$	$S \leq 12$	$S > 12$	$S \leq 12$	$S > 12$	$S \leq 12$	$S > 12$
Follow	0.189	0.081	0.217**	0.107	0.174*	0.066	0.024	0.068	0.044	0.072
	(0.122)	(0.054)	(0.085)	(0.094)	(0.094)	(0.096)	(0.076)	(0.063)	(0.066)	(0.071)
Always Partial	0.217*	0.216*	0.210	0.378***	0.136	0.000	0.167	0.133	0.000	0.204**
	(0.113)	(0.110)	(0.137)	(0.143)	(0.093)	(0.048)	(0.115)	(0.109)	(0.062)	(0.099)
Always Full	0.000	0.043	0.000	0.000	0.000	0.000	0.035	0.000	0.000	0.000
	(0.005)	(0.056)	(0.022)	(0.007)	(0.002)	(0.011)	(0.049)	(0.006)	(0.010)	(0.001)
Always None	0.000	0.000	0.000	0.000	0.041	0.000	0.087	0.087	0.000	0.000
	(0.001)	(0.040)	(0.006)	(0.005)	(0.028)	(0.000)	(0.064)	(0.068)	(0.008)	(0.004)
Partial/None	0.310**	0.446***	0.460***	0.409***	0.370***	0.042	0.315*	0.351**	0.296**	0.302*
	(0.125)	(0.121)	(0.117)	(0.152)	(0.106)	(0.061)	(0.184)	(0.163)	(0.134)	(0.174)
Information Rent	0.000	0.077	0.114	0.056	0.075	0.893***	0.134	0.173**	0.568***	0.353**
	(0.043)	(0.057)	(0.081)	(0.054)	(0.062)	(0.103)	(0.126)	(0.081)	(0.163)	(0.156)
Full Extraction	0.284	0.137	0.000	0.049	0.204	0.000	0.237	0.188	0.092	0.070
γ	0.655***	0.544***	0.605***	0.524***	0.647***	0.482***	0.876***	0.590***	0.591***	0.519***
	(0.100)	(0.106)	(0.102)	(0.099)	(0.119)	(0.073)	(0.194)	(0.079)	(0.115)	(0.082)
β	0.697	0.759	0.723	0.771	0.701	0.799	0.610	0.732	0.731	0.775

Note: Bootstrapped standard errors in parentheses. Level of Significance: ***-1 percent; **-5percent; *-10 percent.

References

DAL BÓ, P. AND G. R. FRÉCHETTE (2011): "The evolution of cooperation in infinitely repeated games: Experimental evidence," *American Economic Review*, 101, 411–429.

EMBREY, M., G. FRÉCHETTE, AND E. STACCHETTI (2013): "An Experimental Study of Imperfect Public Monitoring: Efficiency versus Renegotiation-Proofness," .

FUDENBERG, D., D. RAND, AND A. DREBER (2010): "Slow to anger and fast to forgive: Cooperation in an uncertain world," *American Economic Review*.

VESPA, E. (2016): "An Experimental Investigation of Strategies in Dynamic Games," UCSB working paper.