Online Appendix for

"An Experiment on Social Learning with Information Sequencing"

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Contents

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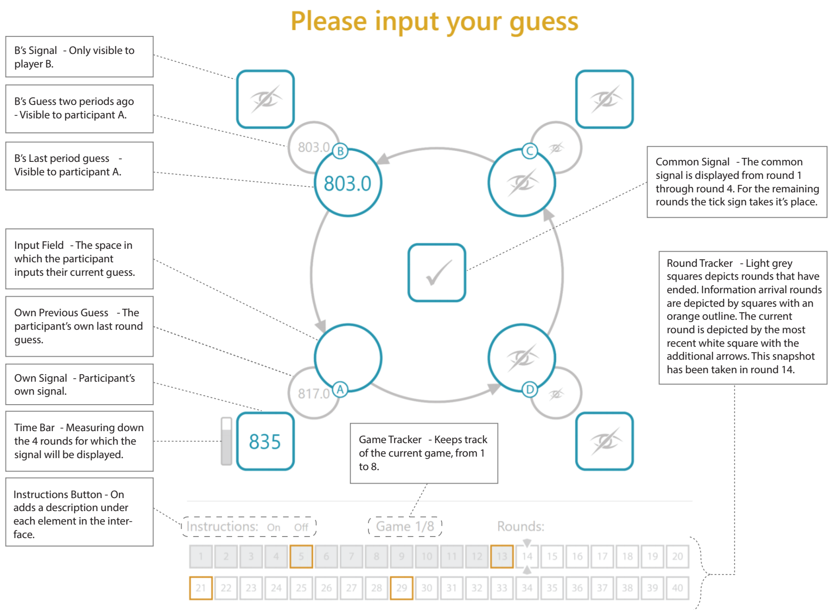
1 Interface

1.1 *Low Information* Treatment Interface

The interface seen by participants in the *Low Information* treatment is shown in Figure 1, with additional text explaining what each component represents(not seen by the participants).

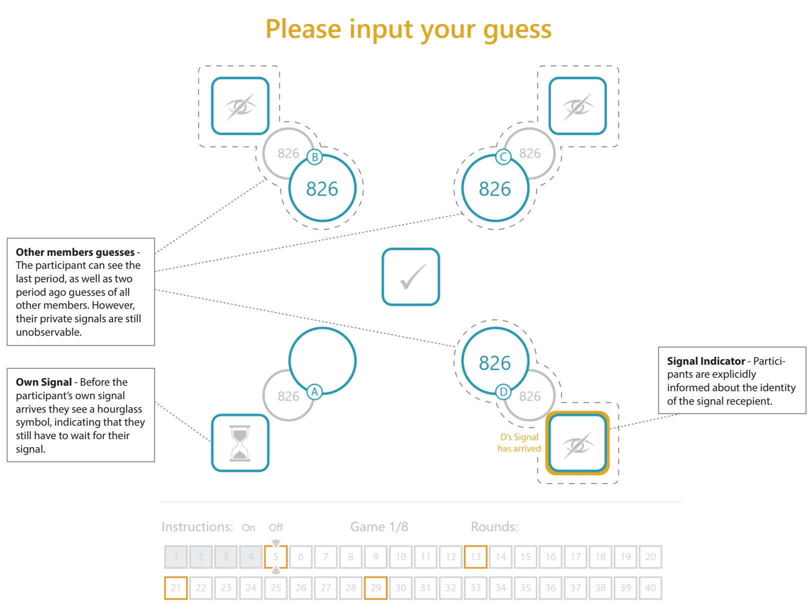
Figure 1: Details of *Low Information* Treatment Interface



1.2 *High Information* Treatment Interface

The interface seen by participants in the *High Information* treatment is shown in Figure 2.

Figure 2: Details of *High Information* Treatment Interface



1.3 Instructions

Instructions were read out loud, and participants could ask clarifying questions throughout. Slides shown in section 1.3.2 and section 1.3.3 went through all relevant rounds from 1 to 40; thus, only a subset is presented here.

1.3.1 Common Instructions for both Treatments

Welcome to

PEXL Princeton Experimental Laboratory for the Social Sciences

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Welcome

PEXL Princeton Experimental Laboratory for the Social Sciences

- Welcome to PExL and thank you for participating in today's experiment.
- Please place all of your personal belongings away so that we can have your complete attention.
- Please use the laptops as instructed. In particular, please do not attempt to browse the web or use programs unrelated to the experiment.

2

Guidelines

- You will be paid in private and in cash at the end of the experiment.
- The amount that you ultimately earn in the experiment depends on your decisions and random chance. You have each earned a $10 payment for showing up on time.
- You will be using laptops for the entire experiment, and all interactions between yourself and others will take place via the laptop's terminal.
- Please DO NOT socialize or talk during the experiment.

3

Number of Games and Rounds

You will play a total of 8 games. Within each game there are 40 rounds.

4

"The Truth"

At the beginning of each game some integer x is drawn from a representative uniform distribution [0,1000].

Let's call this number x "the truth."

Here are a few examples of possible values that x can take:

$x = \{ 690 , 893 , 132 , 504 , 221 , 914 , 351 , 67 , 758 , 435 \ldots \}$

One such value will be selected for each game.

5

The Goal

At the beginning of each game you will be matched with 3 other participants. Your goal is to figure out "the truth" (the value of x).

You will be assigned a letter A, B, C or D. This letter will remain unchanged throughout all games.

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The Common Signal

In round 1, all four participants in the group will receive a common signal.
This signal is the same for all four participants in the group

This signal is drawn from a representative normal distribution with a standard deviation of 30 around "the truth." That is to say, the truth is somewhat close to this signal.

As an example let's say the value of x is 772. Examples of possible values for the common signal are:

$S_{com} = \{ 779 , 793 , 724 , 793 , 773 , 814 , 749 , 722 , 810 , 805 \ldots \}$

As can be seen, although S_{com} is not quite equal to x it is a good indicator of what the value of x might be.

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Private Signals

In addition to the common signal, each participant will also receive a private signal.

Participant A receives private signal S_A
Participant B receives private signal S_B
Participant C receives private signal S_C
Participant D receives private signal S_D.

Unlike the common signal, these signals are privately observed by the receivers.

These signals are also drawn from a representative normal distribution with a standard deviation of 30 around "the truth" . That is to say, the truth is somewhat close to this signal.

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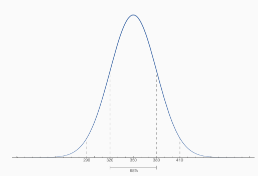
Normal Distribution: Standard Deviation=30



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Examples

Here are some examples of possible values of "the truth" x , the common signal S_{com}, as well as the private signals S_A , S_B , S_C, and S_D:

Example 1: $x = 895$ $S_{com} = 914$ $S_A = 841$ $S_B = 926$ $S_C = 920$ $S_D = 888$

Example 2: $x = 389$ $S_{com} = 438$ $S_A = 398$ $S_B = 412$ $S_C = 379$ $S_D = 370$

Example 3: $x = 781$ $S_{com} = 735$ $S_A = 757$ $S_B = 755$ $S_C = 781$ $S_D = 807$

Example 4: $x = 161$ $S_{com} = 128$ $S_A = 113$ $S_B = 169$ $S_C = 92$ $S_D = 193$

Each one of the signals, the private ones and the common signal, are equally precise.

10

Private Signal Arrival

Unlike the common signal, that will always arrive on round 1, the private signals arrive in rounds 5, 13, 21 or 29. We will call these rounds the "signal rounds."

You will be told exactly when each member receives their private signal.

- In 6 out of 8 games one signal arrives in round 5, one signal arrives in round 13, one signal arrives in round 19 and one signal arrives in round 23.
- In 2 out of 8 games all private signals arrive in round 5.

11

Payment

- You will be paid for three randomly chosen games. Within these games, a single round will be chosen randomly for the payment.
- Your payment will be calculated as follows:

$$payment = \$10 - \frac{1}{4} \cdot |\ guess - \ truth\ |$$

- Simply put, the closer your guess is to the truth, the higher your payment will be.

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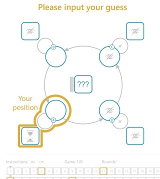
1.3.2 Remaining *Low Information* Treatment Instructions

The Interface

Please input your guess



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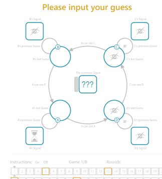
The Interface

Please input your guess



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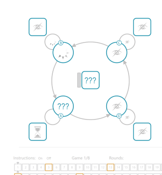
The Interface



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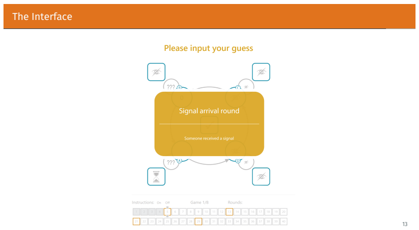
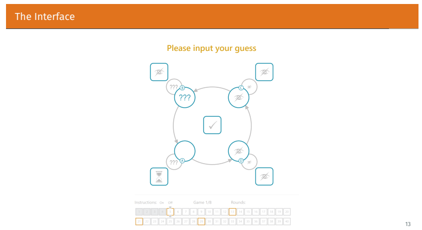
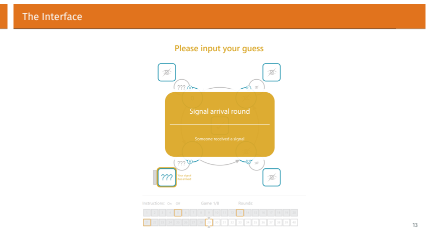
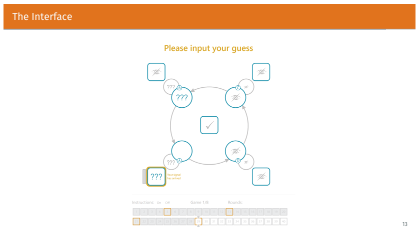
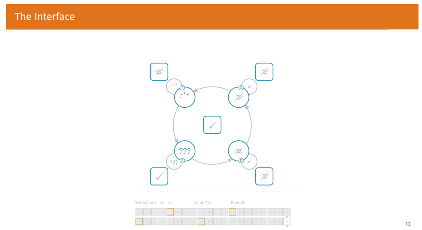
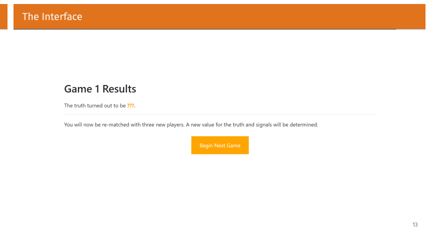


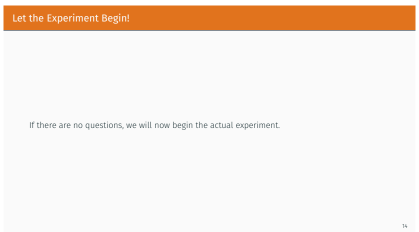




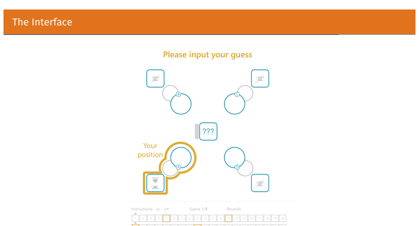


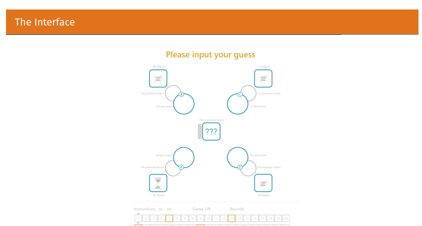


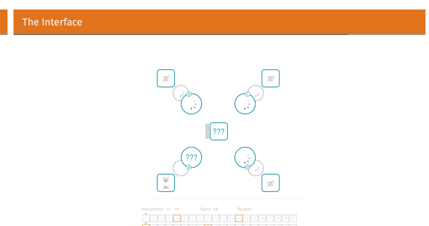


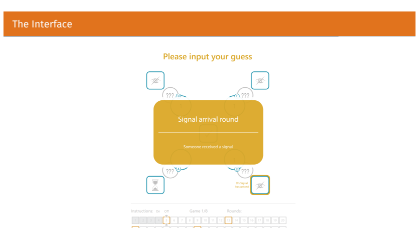


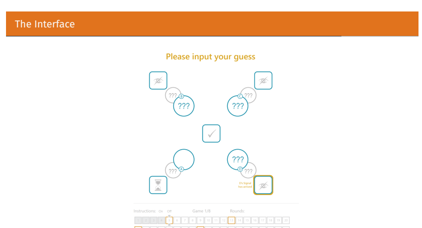
1.3.3 Remaining *High Information* Treatment Instructions

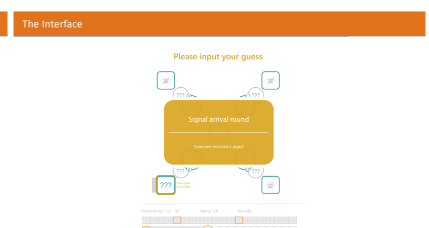


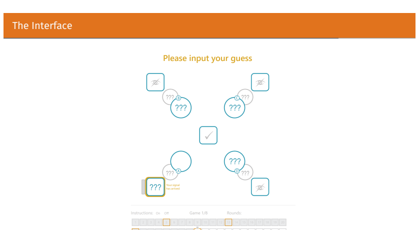


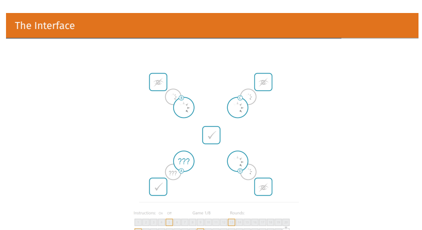


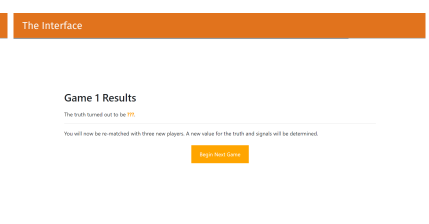


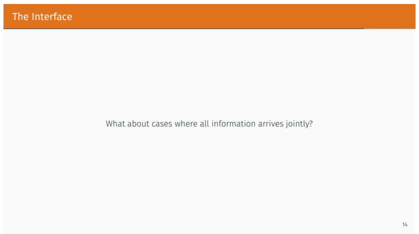


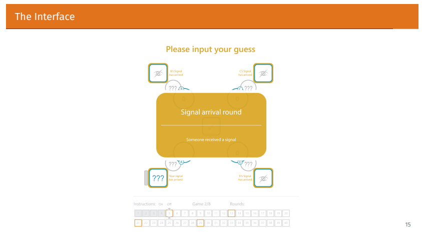


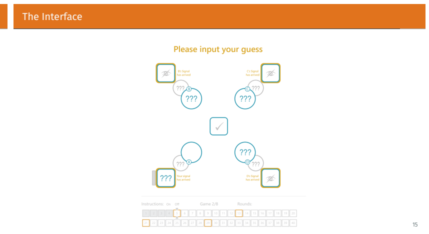


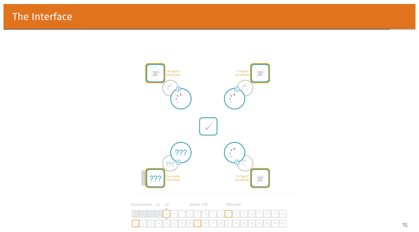


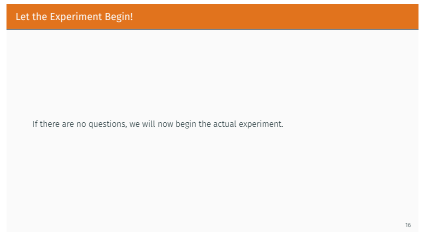










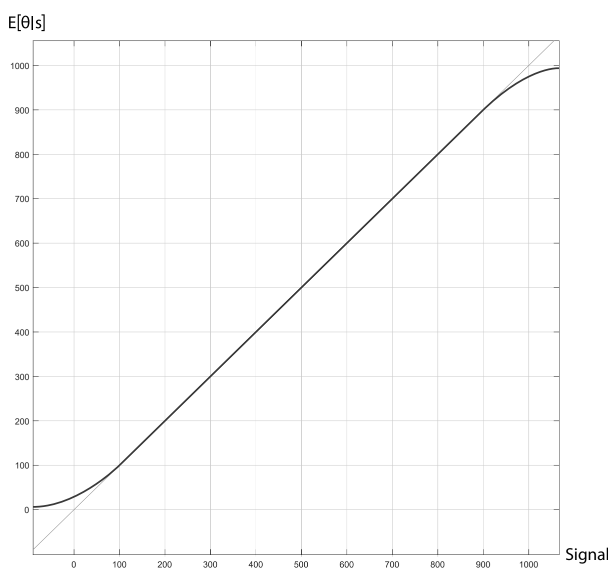


2 Related Data Analysis

2.1 Optimal Guess given a Signal

Because the values θ can take are bounded between 0 and 1000, although signals are unbiased, if the signal value goes beyond these boundaries (or is close to them), the expected conditional θ value is no longer equal to the signal realization, $\mathbb{E}[\theta|s] \neq s$. The graph below plots the optimal guess conditional on a realized signal.

Figure 3: Noisy Bayesian Behavior



As emphasized in the main text, since the realized value of θ plays no role in the identification, its values are drawn once and set to $\{455, 793, 312, 126, 202, 871, 312, 644, 542\}$. The lowest of these values is 126, while the highest is 871. Thus, all values are substantially away from the boundaries so as to make deviations of $\mathbb{E}[\theta|s]$ from the 45-degree line imperceptible.

2.2 Particiapnts' Mistakes

In some cases, it is rather clear that participants make mistakes. For example, consider a participant who, in rounds 20 through 25, inputs the following values $\{875, 875, 875, 87, 875\}$. Clearly, the 87 value was inputted by mistake. We want to deal with these cases to ensure that the results we capture are not driven by such mistakes.

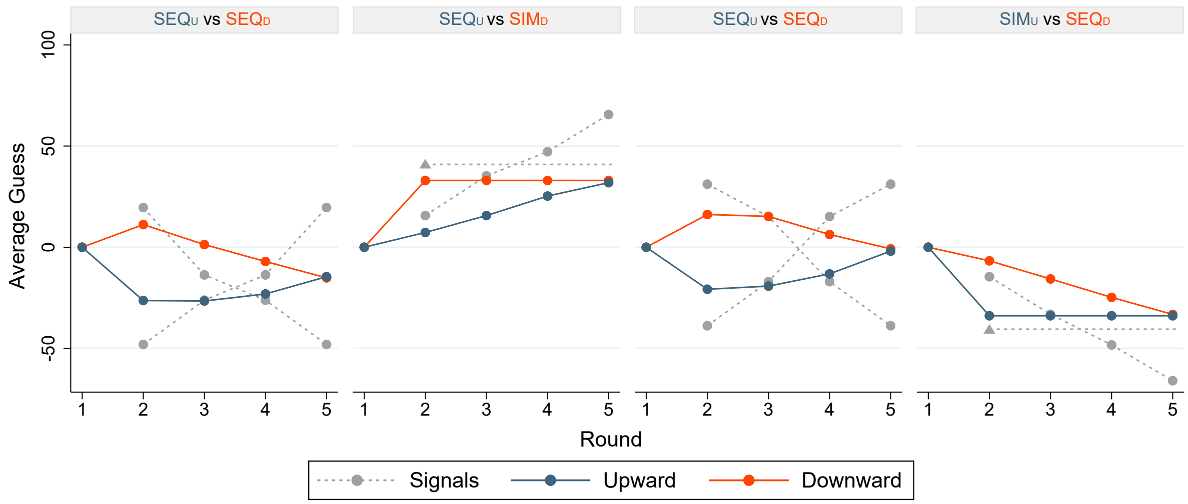
Recall from the main text that the expected range for five normally distributed signals with a standard deviation of 30 is approximately 70. Thus, guesses are rarely, if ever, expected to change for more than 75 points. For each participant in each game, we calculate the mean guesses and replace a guess $g_{i,t}$ with a guess from one round before $g_{i,t-1}$ if the difference from $g_{i,t}$ and the mean is greater than 75(above or below). Thus, we allow for more than twice the expected range in the inputted guesses. This data cleaning procedure would have flagged the 87 value in the above example and would have replaced it with the value inputted one round before, namely 875.

This procedure affects a total of 157 observations out of 20480. We find that results remain qualitatively unchanged if we leave these observations unchanged, replace them with the previous round observations (as we do), or drop them altogether. All things considered, we remain confident that a few mistakes participants make are not the driving force of any of the results we highlight.

2.3 Noisy Bayesian Behavior

In the main text we presented the behavior of Bayesian agents faced with the exact data utilized in the lab. This revealed that, regardless of which sequence pairing we looked at, the final beliefs converged to the same point. Thus, the timing and order of signals played no role in the final beliefs that emerged. However, it seems natural to see how behavior looks for Bayesian agents that might make mistakes (implementation errors). The goal of this section is to see whether errors alone can account for the documented differences. We simulate Bayesian noisy behavior by adding implementation error on the signal incorporation weights ($\lambda_{i,t}$ weights), as well as on the weights placed on others' observable actions ($m_{i,j}$ weights). The graph below presents the average results for the matched sequences in the fully connected network.

Figure 4: Noisy Bayesian Behavior



To construct the above graphs, we follow the same methodology as in Section 4.1 in the main text. The only difference is the added implementation noise on the signal incorporating weights and on the weights placed on others observable choices.

As can be seen, results look almost indistinguishable from the Bayesian behavior with no noise. Importantly, on average, the final beliefs from upward sequences converge to the same level as the final beliefs from the downward sequences, even with noisy implementations. In the graph above, errors are normally distributed with a standard deviation of 0.15 (note that the weights often deviate by as much as 0.40). Considering that these weights can be between 0 and 1, this is an astonishing amount of implementation error, yet, we still see no differences on average from the Bayesian behavior. Results remain unchanged even for higher error levels, and naturally, results remain unchanged when we reduce implementation errors.

Following the same procedure in the ring network leads to the same results. Regardless of the amount of implementation noise, we fail to generate a gap in the final beliefs. Thus, the observed gap between the upward and downward sequences can not be an artifact of noisy implementation.

2.4 Additional Sequence Influence Regressions

To make sure that the statistical significance documented in **Table 2** in the main text is not driven by pooling the observed data across different rounds, Table 1 reports a regression utilizing only data in the 36$^{\text{th}}$ round, which had the lowest fixed effect. As can be seen, once again, the results are highly statistically significant. Almost identical results are obtained if instead only data from the 32nd, 33rd, 34th, or the 35th round are utilized.

Table 1: Sequence Influence

	$\triangle$ *Guess*: Round 36		
	(No Cluster)	(Individual Cluster)	(Group Cluster)
Constant	6.854***	6.854***	6.854***
	(0.000)	(0.000)	(0.000)
Sequential	-0.194	-0.194	-0.194
	(0.913)	(0.884)	(0.932)
Low Info	-1.171	-1.171	-1.171
	(0.523)	(0.545)	(0.663)
Sequential × *Low Info*	0.488	0.488	0.488
	(0.851)	(0.850)	(0.899)
N	544	544	544

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Once more, the main effect captured by the constant is statistically significant, whereas the difference between the treatments and the sequences seems not to be statistically different from zero. On the other hand Table 2 presents a regression utilizing only the last four rounds.

Table 2: Sequence Influence

	$\triangle$ *Guess*: Round 37-40		
	(No Cluster)	(Individual Cluster)	(Group Cluster)
Constant	6.789***	6.789***	6.789***
	(0.000)	(0.000)	(0.000)
Sequential	0.302	0.302	0.302
	(0.740)	(0.795)	(0.886)
Low Info	-0.354	-0.354	-0.354
	(0.706)	(0.836)	(0.884)
Sequential × *Low info*	-3.809***	-3.809	-3.809
	(0.004)	(0.149)	(0.287)
Round Fixed Effects	Yes	Yes	Yes
N	2176	2176	2176

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

None of the round fixed effects appear statistically significant.

2.5 The Weight of Early and Delayed Signals

The table below reports the same regression as in **Table 2** in the main text while utilizing only data from round 36.

Table 3: Weight on Signals: Round 36

	Guess					
	Low Information Treatment			*High Information Treatment*		
	(No C)	(Individual C)	(Group C)	(No C)	(Individual C)	(Group C)
S_c	0.293***	0.293***	0.293***	0.230***	0.230***	0.230***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
S_i	0.149***	0.149***	0.149***	0.156***	0.156***	0.156***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$AdditionalWeight$	0.0542***	0.0542***	0.0542**	0.0729***	0.0729***	0.0729***
	(0.002)	(0.001)	(0.017)	(0.000)	(0.000)	(0.000)
N	384	384	384	432	432	432

p-values in parentheses

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

As can be seen, although some statistical power is lost by utilizing a smaller fraction of the data, the sign and statistical significance of the *Additional Weight* variable remains unchanged. Similar values are derived for any of the relevant rounds.

2.6 Weight on the Common Signal

Below we present the full regression table, a part of which was presented on **Table 3** in the main text. In the regression below, S corresponds to the signal the participant receives, whereas S_{Ni} corresponds to the signal i'th indirect neighbor of the participant receives. As was the case in the main text, S_c corresponds to the common signal; SEQ is an indicator variable equal to one if the data comes from a game in which information was released sequentially, while HIT is an indicator variable equal to one if the data comes from the high information treatment. SIM is simply $1 - SEQ$.

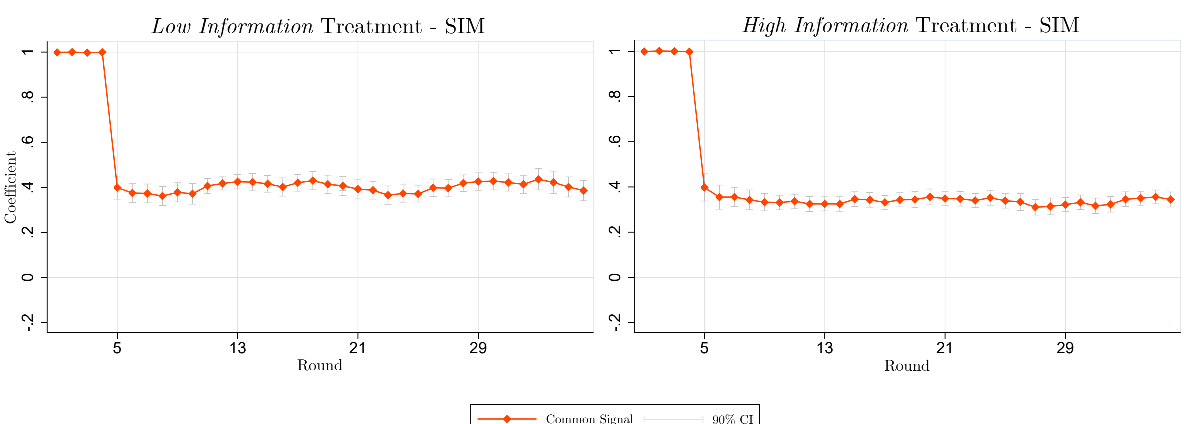
It would be natural to suspect that, to some extent, the greatly exaggerated influence of the common signal, as depicted in **Figure 4** in the main text, is driven by the low Information treatment, in which, perhaps, participants could not deduce that they are in a round in which all information was released jointly in round 5. If this was the case, then had participants known that all information was released in round 5, they would have done a much better job in discounting the common signal, and thus, its weight would not have been so greatly exaggerated. However, in the high information treatment, when information arrives simultaneously, participants are explicitly informed that all signals have arrived jointly. In this treatment, they can clearly see that all other participants have received their signals in round 5. Hence, if it was improper deduction with regard to being in a sequential information release round versus a joint information release round, this effect should not exist in the high Information treatment. Figure 5 shows the influence that the common signal has in each round in the low Information treatment (on the left) and in the high Information treatment (on the right), in rounds in which all signals were released jointly.

Table 4: Weight on Common Signal - Full Regression

	Guess: Round 32-36			*Guess*: Round 36		
	(No C)	(Individual C)	(Group C)	(No C)	(Individual C)	(Group C)
S_c	0.412***	0.412***	0.412***	0.385***	0.385***	0.385***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$S_c \times SIM \times HIT$	-0.0677***	-0.0677**	-0.0677	-0.0409	-0.0409	-0.0409
	(0.000)	(0.025)	(0.159)	(0.210)	(0.235)	(0.429)
$S_c \times SEQ$	-0.159***	-0.159***	-0.159***	-0.122***	-0.122***	-0.122**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.014)
$S_c \times SEQ \times HIT$	-0.0737***	-0.0737***	-0.0737**	-0.0716**	-0.0716**	-0.0716*
	(0.000)	(0.006)	(0.032)	(0.015)	(0.012)	(0.052)
$S \times SEQ \times LIT$	0.331***	0.331***	0.331***	0.300***	0.300***	0.300***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$S \times SIM \times LIT$	0.224***	0.224***	0.224***	0.244***	0.244***	0.244***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$S \times SEQ \times HIT$	0.277***	0.277***	0.277***	0.270***	0.270***	0.270***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$S \times SIM \times HIT$	0.228***	0.228***	0.228***	0.217***	0.217***	0.217***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$S_{N1} \times SEQ \times LIT$	0.230***	0.230***	0.230***	0.233***	0.233***	0.233***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$S_{N1} \times SIM \times LIT$	0.185***	0.185***	0.185***	0.184***	0.184***	0.184***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$S_{N1} \times SEQ \times HIT$	0.188***	0.188***	0.188***	0.188***	0.188***	0.188***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$S_{N1} \times SIM \times HIT$	0.116***	0.116***	0.116***	0.139***	0.139***	0.139***
	(0.000)	(0.002)	(0.000)	(0.001)	(0.001)	(0.000)
$S_{N2} \times SEQ \times LIT$	0.122***	0.122***	0.122***	0.135***	0.135***	0.135***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$S_{N2} \times SIM \times LIT$	0.0870***	0.0870*	0.0870**	0.0798**	0.0798*	0.0798**
	(0.000)	(0.060)	(0.027)	(0.039)	(0.095)	(0.023)
$S_{N2} \times SEQ \times HIT$	0.167***	0.167***	0.167***	0.177***	0.177***	0.177***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$S_{N2} \times SIM \times HIT$	0.142***	0.142***	0.142***	0.149***	0.149***	0.149***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$S_{N3} \times SEQ \times LIT$	0.0617***	0.0617***	0.0617***	0.0665***	0.0665***	0.0665***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.003)	(0.000)
$S_{N3} \times SIM \times LIT$	0.0897***	0.0897***	0.0897***	0.102***	0.102**	0.102***
	(0.000)	(0.005)	(0.001)	(0.008)	(0.016)	(0.003)
$S_{N3} \times SEQ \times HIT$	0.188***	0.188***	0.188***	0.172***	0.172***	0.172***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$S_{N3} \times SIM \times HIT$	0.169***	0.169***	0.169***	0.150***	0.150***	0.150***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	5440	5440	5440	1088	1088	1088

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 5: The Common Signal's Influence by Treatment



The graphs above represent the influence that the common signal has on the guesses in each round. The graphs also show the 95% confidence interval of the estimated weight.

As can be seen, in both treatments, the common signal loses a substantial amount of influence exactly in round 5, when all the private signals are released. Afterward, this value, to a large extent, remains unchanged.

2.7 Parameter Estimation

In both treatments, for a clear distinction between the estimated parameters, we utilize data from games in which information was released sequentially.

Low Information Treatment To identify the weight agents place on their private signal when it arrives, we focus on the rounds in which the agent receives a signal. We regress the guess $g_{i,t}$ formed when the agent received their private signal on her previous guess $g_{i,t-1}$, on the previous guess of the neighbor she observes $g_{k,t-1}$, the common signal s_c and her private signal s_i. The coefficient on s_i identifies the weight the agent places on her signal. We run this regression separately for signals that arrive in rounds 5, 13, 21, and 29. Each column in Table 5 corresponds to one such regression.

Table 5: $\lambda^{\tilde{t}}$ Values: *Low Information Treatment*

	$g_{i,t}$			
	$\tilde{t}=5$	$\tilde{t}=13$	$\tilde{t}=21$	$\tilde{t}=29$
$g_{i,t-1}$	0.216*	0.245*	0.192*	0.384**
	(0.056)	(0.073)	(0.087)	(0.012)
$g_{j,t-1}$	0.0542	0.106	-0.00833	0.0476
	(0.442)	(0.325)	(0.936)	(0.697)
s_i	0.604***	0.614***	0.595***	0.539***
	(0.000)	(0.000)	(0.000)	(0.000)
s_c	0.125	0.0337	0.217***	0.0270
	(0.349)	(0.579)	(0.003)	(0.746)
N	96	96	96	96

p-values in parentheses
Individual-level clustering
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Thus the values of $\lambda_{\hat{t}}$, the weights the participants place on their signals on the different information rounds, are $\{0.604, 0.614, 0.595, 0.539\}$. Importantly, note that had we run these regressions jointly by estimating a single coefficient for $g_{i,t-1}$, $g_{j,t-1}$, and s_c, we would force the estimated s_i parameters to be similar across rounds.[1] For example, when estimating the above parameters jointly, the estimated parameters on s_i are $\{0.584, 0.583, 0.581, 0.581\}$, which are much closer to one another than the values presented in Table 5. However, this

[1] In a joint estimation this can be avoided by interacting each variable with the round in which information arrives. This would lead to a regression with sixteen variables, which would effectively be equivalent to the separate regressions.

is an anomaly of the additional, unnecessary restrictions on $g_{i,t-1}$, $g_{j,t-1}$, and s_c. We run each regression separately to avoid such anomalies, thus giving maximum flexibility for any differences to show up.

We next estimate the remaining parameter values. The first column in Table 6 regresses the guess of participant i in time t on her previous guess, her neighbor's previous guess, her private signal as well as the common signal, utilizing only rounds in which the participant, or her neighbor, has not received any new information, be it directly or indirectly. This identifies the weight agents place on their previous guess, as well as on the guess of their neighbor in such rounds. Thus we estimate $m_{i,i} = 0.657$ and $m_{i,j} = 0.248$. The second column utilizes data from rounds in which the participant's neighbor receives information. Consequently, the coefficient of $\overline{g}_{j,t-1}$ represents the weight a participant places on her neighbor when the neighbor receives new information, while the new parameter value on $g_{i,t-1}$ represents the value the participant places on herself in such rounds. These lead to the estimation of $\underline{m}_{i,i} = 0.467$ and $\overline{m}_{i,j} = 0.471$.

Table 6: Parameter Values: *Low Information Treatment*

	$g_{i,t}$		
$g_{i,t-1}$	0.657***		0.610***
	(0.000)		(0.000)
$g_{j,t-1}$	0.248***		0.208***
	(0.000)		(0.000)
$\underline{g}_{i,t-1}$		0.467***	
		(0.000)	
$\overline{g}_{j,t-1}$		0.471***	
		(0.000)	
s_i	0.0562***	0.0471***	0.130***
	(0.000)	(0.000)	(0.000)
s_c	0.0384***	0.0151	0.0521***
	(0.000)	(0.472)	(0.000)
N	12288	1152	8256

p-values in parentheses
Individual-level clustering
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Finally, the last column in Table 6 utilizes only data from rounds after the participant has received her private signal. Thus, the coefficient on s_i and s_c reveal the anchoring parameters, namely $\delta_s = 0.13$ and $\delta_c = 0.0521$.

High Information Treatment The estimation of the parameters in the high information treatment is almost identical to the one described above. However, here $g_{j,t-1}$ represents the sum of the guesses of the three group members. This makes it so that we estimate only one parameter instead of separate parameters for each neighbor. We find this reasonable since, from the participant's point of view, there is no distinction between her observable group members. Table 7 reveals the estimated parameters $\lambda_{\hat{t}} = \{0.706, 0.575, 0.642, 0.612\}$.

Table 7: $\lambda^{\tilde{t}}$ Values: *High Information Treatment*

	$g_{i,t}$			
	$\tilde{t}=5$	$\tilde{t}=13$	$\tilde{t}=21$	$\tilde{t}=29$
$g_{i,t-1}$	0.198	0.322**	0.118	-0.213
	(0.156)	(0.019)	(0.552)	(0.354)
$g_{j,t-1}$	0.0511	0.0132	0.0693	0.145*
	(0.328)	(0.744)	(0.284)	(0.055)
s_i	0.706***	0.575***	0.642***	0.612***
	(0.000)	(0.000)	(0.000)	(0.000)
s_c	-0.0614	0.0617	0.0315	0.162*
	(0.714)	(0.134)	(0.628)	(0.061)
N	108	108	108	108

p-values in parentheses
Individual-level clustering
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

While Table 8 reveal the estimated parameters $m_{i,i} = 0.568$, $m_{i,j} = 0.128$ from the first column; $\underline{m}_{i,i} = 0.312$, $\underline{m}_{i,j} = 0.0658$ and $\overline{m}_{i,j} = 0.497$ from the second column; $\delta_i = 0.0675$ and $\delta_c = 0.0201$ from the third column.

Table 8: Parameter Values: *High Information Treatment*

	$g_{i,t}$		
$g_{i,t-1}$	0.568***		0.547***
	(0.000)		(0.000)
$g_{j,t-1}$	0.128***		0.122***
	(0.000)		(0.000)
$\underline{g}_{i,t-1}$		0.312***	
		(0.000)	
$\underline{g}_{j,t-1}$		0.0658***	
		(0.002)	
$\overline{g}_{j,t-1}$		0.497***	
		(0.000)	
s_i	0.0281***	0.0358***	0.0675***
	(0.000)	(0.000)	(0.000)
s_c	0.0197***	0.0234	0.0201***
	(0.001)	(0.142)	(0.004)
N	13824	1296	9936

p-values in parentheses
Individual-level clustering
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.8 Best Response to Data

The main estimation utilizes games in which information is released sequentially, allowing for the separate estimation of the parameters of interest. Having estimated the parameters of the model, it is then of interest to ask what would be the best response to the observed data. If a *Bayesian* agent were to participate in this experiment, knowing that this is exactly the pool of players they would face, what would be their best response? The values of the best response parameters are reported in Table 9. A quick glance reveals that the best response to the data differs from the estimated parameters. These optimal weights are calculated for the *high information treatment*, similar weights are obtained for the *low information treatment*.

Table 9: Best Response to the Data

	Weight on Private Signal			
	λ_5	λ_{13}	λ_{21}	λ_{29}
Value	$1/2$	$1/3$	$1/4$	$1/5$

	Weight on own Previous Guesses				Anchoring Parameters	
	$m_{i,i}$	$m_{i,j}$	$\underline{m}_{i,i}$	$\overline{m}_{i,j}$	δ_c	δ_s
Value	1	0	0.50	0.50	0	0

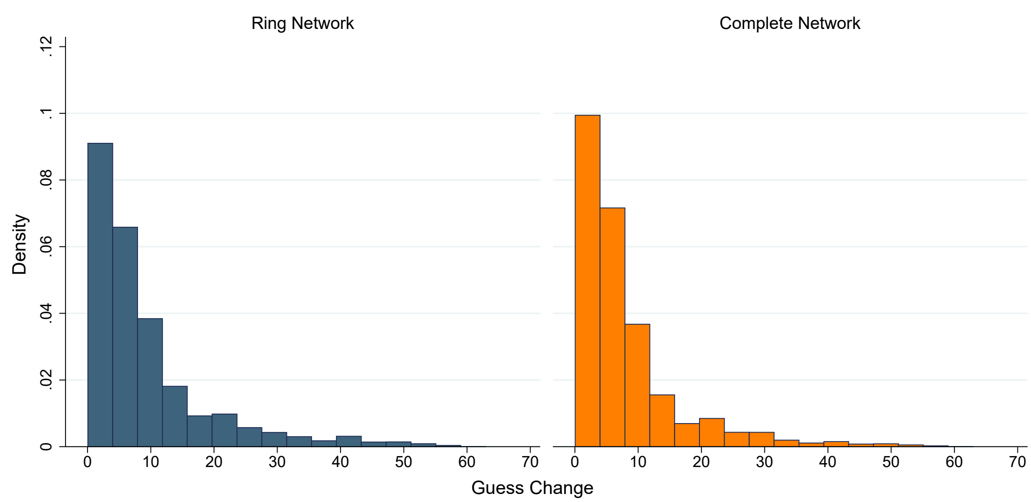
As can be seen, even when faced with agents who are not Bayesians, there is no reason to deviate from the Bayesian optimal weights on the private signal. Furthermore, there is no reason to anchor on the common or the private signal, thus $\delta_c = \delta_s = 0$. On the other hand, since there is no more immediate convergence in rounds with no new information, the Bayesian player would no longer be indifferent on which past guesses to follow. It would be optimal to place weight one on one's own guess and zero on all other participants' guesses. Finally, one round after a participant has received information, it is no longer optimal to place full weight on that participant; rather, it is now optimal on average to place weight 0.50 on them. This comes as a result of participants' over-reacting to their own signals. In fact, the optimal weight to place on the guess of a participant who just received a signal is time-dependent, in particular, $\overline{m}^6_{i,j} = 0.71$, $\overline{m}^{14}_{i,j} = 0.59$, $\overline{m}^{22}_{i,j} = 0.39$, and $\overline{m}^{30}_{i,j} = 0.30$. As was seen in the data, participants roughly place weight between 0.57 and 0.70 on their own signal, when they should, in fact, place a decreasing weight the later they receive the signal. To correct this, best responding requires placing a lower weight on the recently informed participant. This weight further decreases for participants who receive their signals in later rounds.

3 Further Data Analysis

3.1 Guess Changes

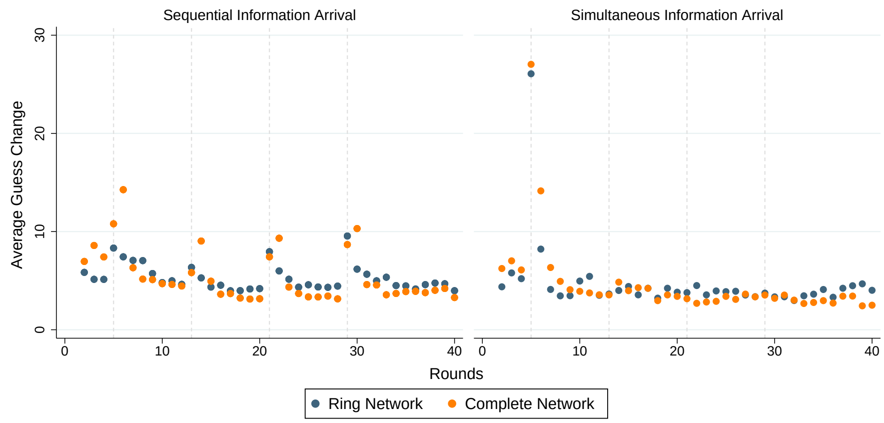
Let $g_{i,r,k}$ represent the guess of participant i in round r of game k. We calculate the absolute value of the round-to-round difference between the guesses, that is $\triangle g_{i,r,k} = |g_{i,r,k} - g_{i,r-1,k}|$, and plot the histogram of these differences in Figure 6 . As can be seen, most of the round-to-round guess changes are relatively small. Some changes in the participants' guesses, however, are more sizable.

Figure 6: Histogram of Absolute Guess Change



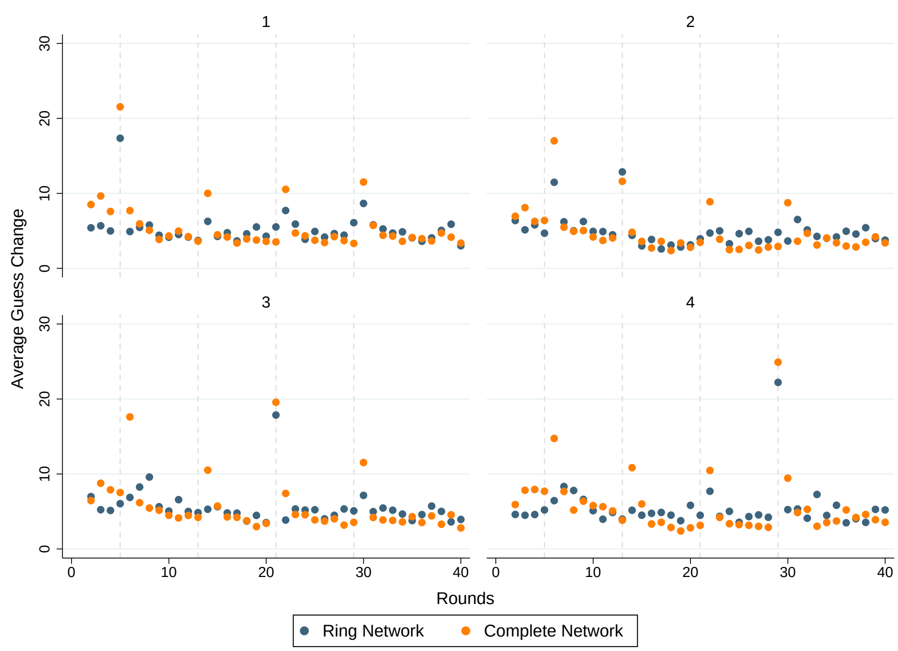
To better understand when these changes take place, we calculate the mean of these differences across individuals and games, $\triangle \overline{g}_r = \frac{1}{IK} \sum_{i=1}^{I} \sum_{k=1}^{K} \triangle g_{i,r,k}$. We do this separately for games in which information arrives sequentially in rounds 5, 13, 21, and 29, as well as games in which all signals arrive simultaneously in round 5. Figure 7 plots these changes. As can be seen, when information is released sequentially, these average differences are higher in the information rounds, whereas when information is released simultaneously, the sizable difference occurs exactly in round 5, when all participants receive their signals.

Figure 7: Average Absolute Guess Change



We further break down these average changes based on when the participant received the signal; these changes are shown in Figure 8. On average, the biggest difference from the previous guess occurs on the round in which the participant receives their private signal.

Figure 8: Average Absolute Guess Change by Signal Arrival



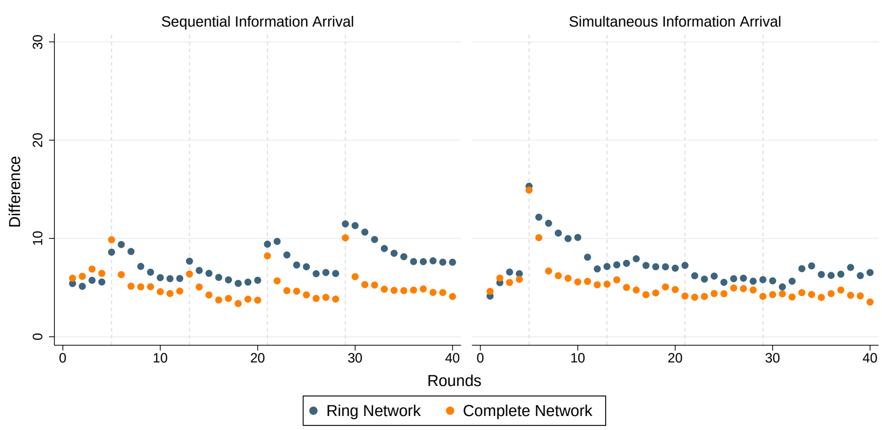
3.2 Convergence

We now seek to see whether the guesses of participants within a group converge in time. Let $z(i,k)$ represent the set of the members of the group to which participant i belongs in game k. We calculate the following [2]:

$$d_{i,r,k} = \frac{1}{I} \sum_{i=1}^{I} \left| g_{i,r,k} - \frac{1}{4} \sum_{j \in z(i,k)}^{4} g_{j,r,k} \right|$$

Figure 9 plots these values for all 40 rounds, separately when information arrives sequentially and simultaneously. As can be seen, for the sequential arrival games, this difference is increased in information arrival rounds and falls between such rounds. For games in which all signals arrive simultaneously, there is a large jump in round 5, when all participants receive their signals. This difference tends to fall for the next few rounds and stabilizes. As can be seen, the guesses of the participants are closer under the complete network.

Figure 9: Average Difference from Group Average Guess



3.3 Gravitation Towards the Signal

We next turn to analyze to what extent participants adjust their guesses toward the latest signal received by a member of the group. Let $\hat{r}_{i,k} \in \{5, 13, 21, 20\}$ represent the round in which signal $s_{i,k}$ arrives for participant i in game k. For each group member, we calculate the difference between their guess and participant i's signal, one round before the signal arrival all the way to 7 rounds after. We average this difference out across participants and normalize it by the average initial difference one round before the signal arrival. Hence, we

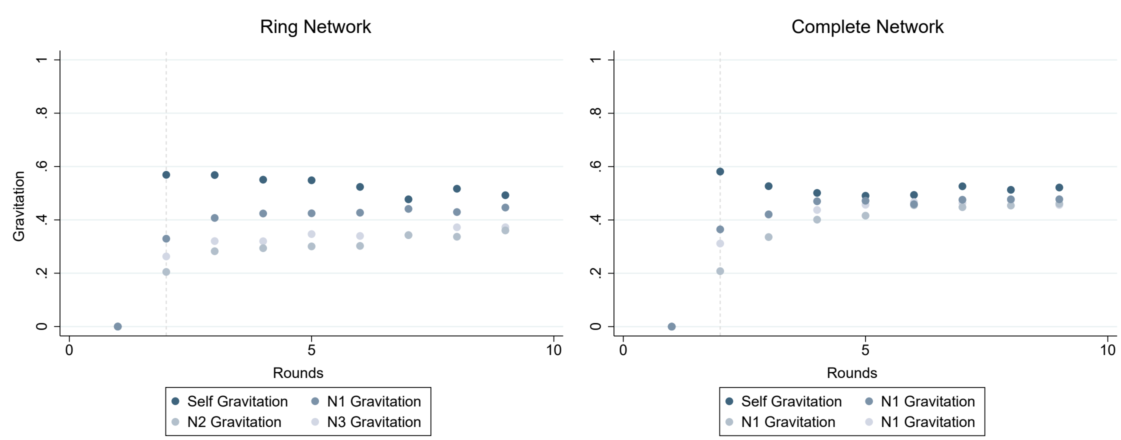
[2] Note that this is just a monotonic transformation of the standard deviation measure.

calculate:

$$d^z_{i,r,k} = 1 - \frac{\frac{1}{I}\sum_i \left(g_{i-z,r,k} - s_{i,k}\right)}{\frac{1}{I}\sum_i \left(g_{i-z,\hat{r}_{i,k}-1,k} - s_{i,k}\right)} \qquad r \in \{\hat{r}_{i,k} - 1, \ldots, \hat{r}_{i,k} + 7\} \qquad z \in \{0, 1, 2, 3\}$$

From the values of $d^0_{i,r,k}$, we see how the participant was influenced by her own signal. Whereas $d^1_{i,r,k}$ informs us how the participant's neighbor, who gets to see her guess with one round delay, is influenced by her signal; All the way to $d^4_{i,r,k}$, which informs us how the participant who is least likely to be influenced by participant i's signal, shifts her guesses. For all values of z, this measure is mechanically equal to 0 one round before the signal arrival. It would remain unmoved from 0 if, on average, participants' guesses did not shift toward the signal at all. If, however, the participants' guesses fully shifted towards the signal, this value would be equal to 1. Values in between inform us about the magnitude to which participants' guesses moved toward the signal. In Figure 10, we see these measures for games in which all signals arrive simultaneously in round 5.

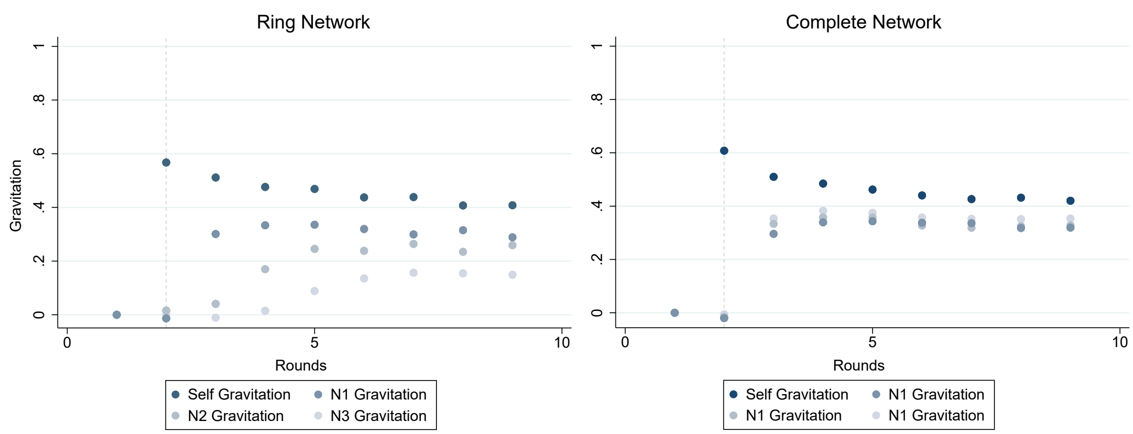
Figure 10: Gravitation Towards the Signal: Simultaneous Signal Arrival



As can be seen, in the ring network, the participant that was most influenced by participant i's signal is participant i herself. With $d^0_{i,\hat{r}_{i,k},k}$ having a value of about 0.58 in the round when the signal is received, which is round 5 for these games. This indicates that, on average, when mixing between their last guess and their newly received signal, participants place weight of about 0.58 on their signal. The value of $d^0_{i,r,k}$ slowly goes down as the participant is influenced by others' guesses and is drawn towards them. From the graph, we can also see that under the ring network, the second most influenced group member is the first neighbor of participant i, who gets to see her guess with one round delay. As expected, for any round, we see a clear ranking of influences from $d^1_{i,\hat{r}_{i,k},k}$ to $d^3_{i,\hat{r}_{i,k},k}$, where the further they are from directly seeing the guess of participant i, the less they are influenced.

On the complete network, however, all neighbors are roughly equally influenced, as they all have equal to each other's past guesses. What may seem surprising is that in the round where participant i receives a signal, the values of $d^z_{i,\hat{r}_{i,k},k}$ for her neighbors are not close to 0. This might seem a surprise at first, as these members could not have been influenced by a signal that only participant i saw that round; however, the explanation for this is rather mechanical. In rounds in which all signals arrive simultaneously, all signals are either above or below the common signal. This correlation makes these values above zero even in the first round. Figure 11, on the other hand, plots these values for games in which information arrives sequentially.

Figure 11: Gravitation Towards the Signal: Sequential Signal Arrival



What becomes clear from the graph above is that, once more, the most influenced agent is the agent who receives the private signal. In the complete network, all other agents are approximately equally affected, as they all have equal access to the changed guesses of the agent who received information. In the ring network, however, the second most influenced participant is the first neighbor of the participant who received the private signal, followed by that neighbor's neighbor. In comparison, the least affected participant is the neighbor's neighbor's neighbor. Thus, in the ring network, as information disseminates in the network, its impact slowly declines.