Beliefs II

October 2, 2020

Research question

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  - I am smart, my sports team will win, etc.
- **Motivated beliefs**
- This belief can be accurate or not

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  - I am smart, my sports team will win, etc.
- **Motivated beliefs**
- This belief can be accurate or not
- Introduce Person 2, who wants to believe the same thing
- **Research question:** When Person 1 and Person 2 exchange their beliefs, do they become more biased?

- OY study people's beliefs about how smart they are
  - Everyone wants to believe they are smart
- Intelligence measured using an IQ test (Raven's matrices)
  - See some examples here: `https://iqpro.org/`
- **Question:** Do people become more biased when they are beliefs about own intelligence?

Experimental design (p. 9)

All sessions consisted of five parts.

1. **Raven's Matrices:** Subjects were shown ten Raven's Progressive Matrices (including a range from relatively easy to relatively difficult matrices) and were given 75 seconds to complete each one. If a Raven's matrix was selected for payment subjects received \$10 if they answered it correctly. In Motivation treatments, scores on these matrices were used to determine group assignment.[10]

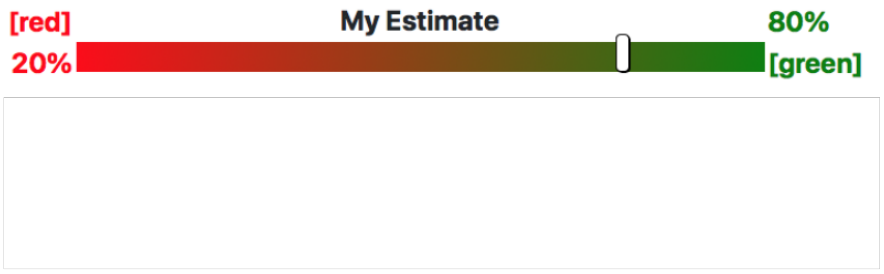
2. **Practice #1:** Subjects participated in an Elicitation task with No Exchange and with random group assignment (with a probability 0.6 of assignment to one group and 0.4 to the other). The purpose of this task (and the task in part 3) is to familiarize subjects with the software and the task.[11]

3. **Practice #2:** Identical to part 2, except that we set a probability of 0.7 of assignment to one group and 0.3 of assignment to the other.

4. **Main Elicitation:** Subjects participated in an Elicitation task that varied with treatment as described below.

5. **Survey:** We asked subjects a number of survey questions including additional cognitive tests, beliefs about others, gender and major.

Elicitation task, seconds 1-44



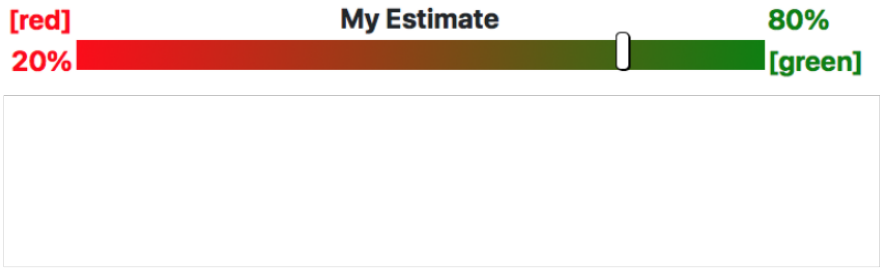
The computer assigned the participants with the

10 lowest scores to red

10 highest scores to green

Your counterpart is in the **same group** as you are and you each must estimate the likelihood you are both in the green group vs. the red group.

Elicitation task, seconds 45-89 NO EXCHANGE



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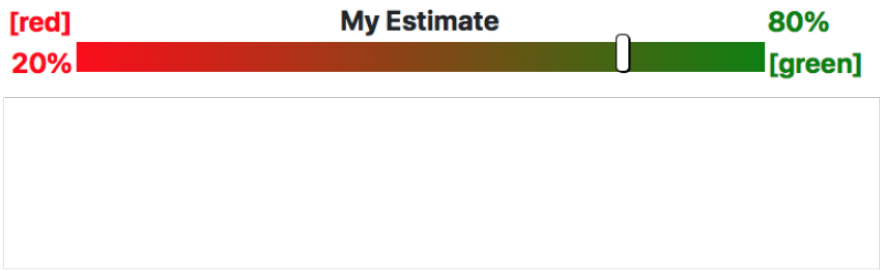
Elicitation task, seconds 90-180 NO EXCHANGE



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Your signal is: RED

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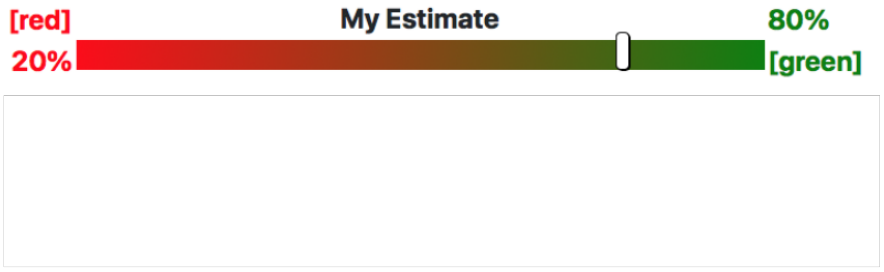

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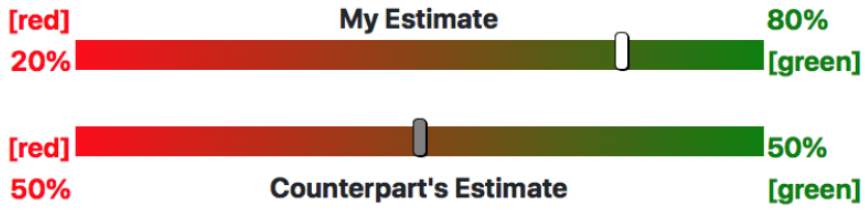

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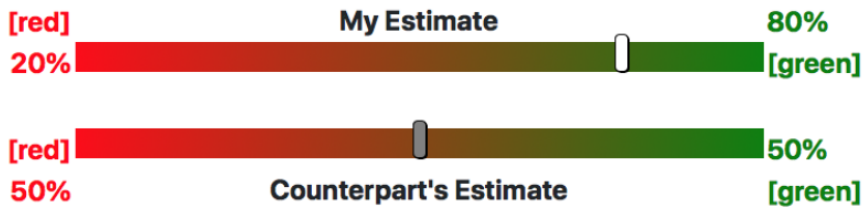

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Your signal is: RED

Treatments (p. 10)

Table 1: Summary of Treatments

	Exchange-Motivation (E-M)	No Exchange-Motivation (NE-M)	Exchange-No Motivation (E-R)
Group Assignment	Based on IQ score	Based on IQ score	Random
Group Composition	10 in Green, 10 in Red	10 in Green, 10 in Red	14 in Green, 16 in Red
Phase 1	No social interaction	No social interaction	No social interaction
Phases 2 & 3	Beliefs public in pairs	No social interaction	Beliefs public in pairs

Treatments differ only in the main elicitation task in Part 4. These differences are described above.

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4. Why give objective signals in Phase 3?

5. Why have the Exchange-No Motivation treatment?

A Note on Belief Elicitation

- Typically, we ask subjects to report a number $X \in [0, 1]$ indicating their subjective probability that some event A is true
- How to pay them for the accuracy of their guess?
- Simplest procedure: **quadratic scoring rule**
- $$P = \begin{cases} r - k * (1 - X)^2 & \text{if A is true} \\ r - k * (X)^2 & \text{otherwise} \end{cases}$$

Incentive comptability

Let p denote the probability subject assigns to A

$$E(P) = p(r - k(1 - X)^2) + (1 - p)(r - kX^2)$$

- At the optimum,

$$\begin{aligned} pk2(1 - X) - (1 - p)k2X = 0 \Leftrightarrow \\ p(1 - X) = (1 - p)X \Leftrightarrow \\ p = X \end{aligned}$$

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Issue: risk-aversion

$EU = p(r - k(1 - X)^2)^\sigma + (1 - p)(r - kX^2)^\sigma \Rightarrow X \neq p$

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- Pay subject if and only if if $S < N$

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- **Advantage:** not affected by attitudes to risk
- **Disadvantage:** difficult to explain

Back to design (p. 9)

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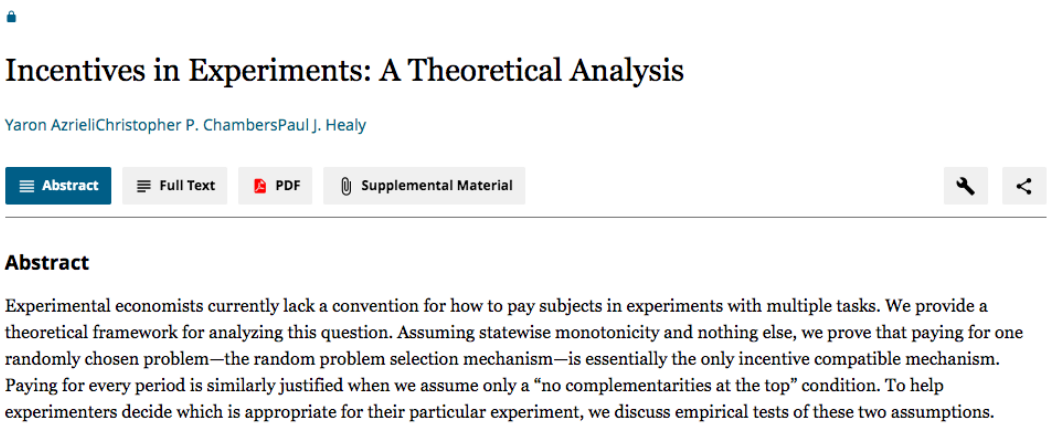
Back to design (p.13)

If part 1 or part 5 was selected for payment, we paid subjects $10 for submitting a correct answer on a randomly selected question from that part. If parts 2-4 were selected for payment, we paid subjects $0 or $10 based on their belief in a randomly selected second (out of 180) using the Binarized Scoring Rule.

- I.e., one decision selected for payment
- Done to avoid hedging across decisions
-



Incentives in Experiments: A Theoretical Analysis

Yaron AzrieliChristopher P. ChambersPaul J. Healy

Abstract | Full Text | PDF | Supplemental Material

Abstract

Experimental economists currently lack a convention for how to pay subjects in experiments with multiple tasks. We provide a theoretical framework for analyzing this question. Assuming statewise monotonicity and nothing else, we prove that paying for one randomly chosen problem—the random problem selection mechanism—is essentially the only incentive compatible mechanism. Paying for every period is similarly justified when we assume only a "no complementarities at the top" condition. To help experimenters decide which is appropriate for their particular experiment, we discuss empirical tests of these two assumptions.

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  - E.g., "subjects in the low IQ group believe, on average, incorrectly, that the likelihood that they are in the high IQ group is greater than 50% ($p < 0.01$)'

  - This statement means that the authors tested the hypothesis that the mean belief is equal to 50% and rejected it at a 99% significance level

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- Example in Stata

Treatment effects

- We can test for treatment effects using a regression framework:

$$y_i = \beta_0 + \beta_1 D_i + \epsilon_i$$

$$D_i = \begin{cases} 1 & \text{if } i \text{ is in treatment} \\ 0 & \text{if } i \text{ is in baseline} \end{cases}$$

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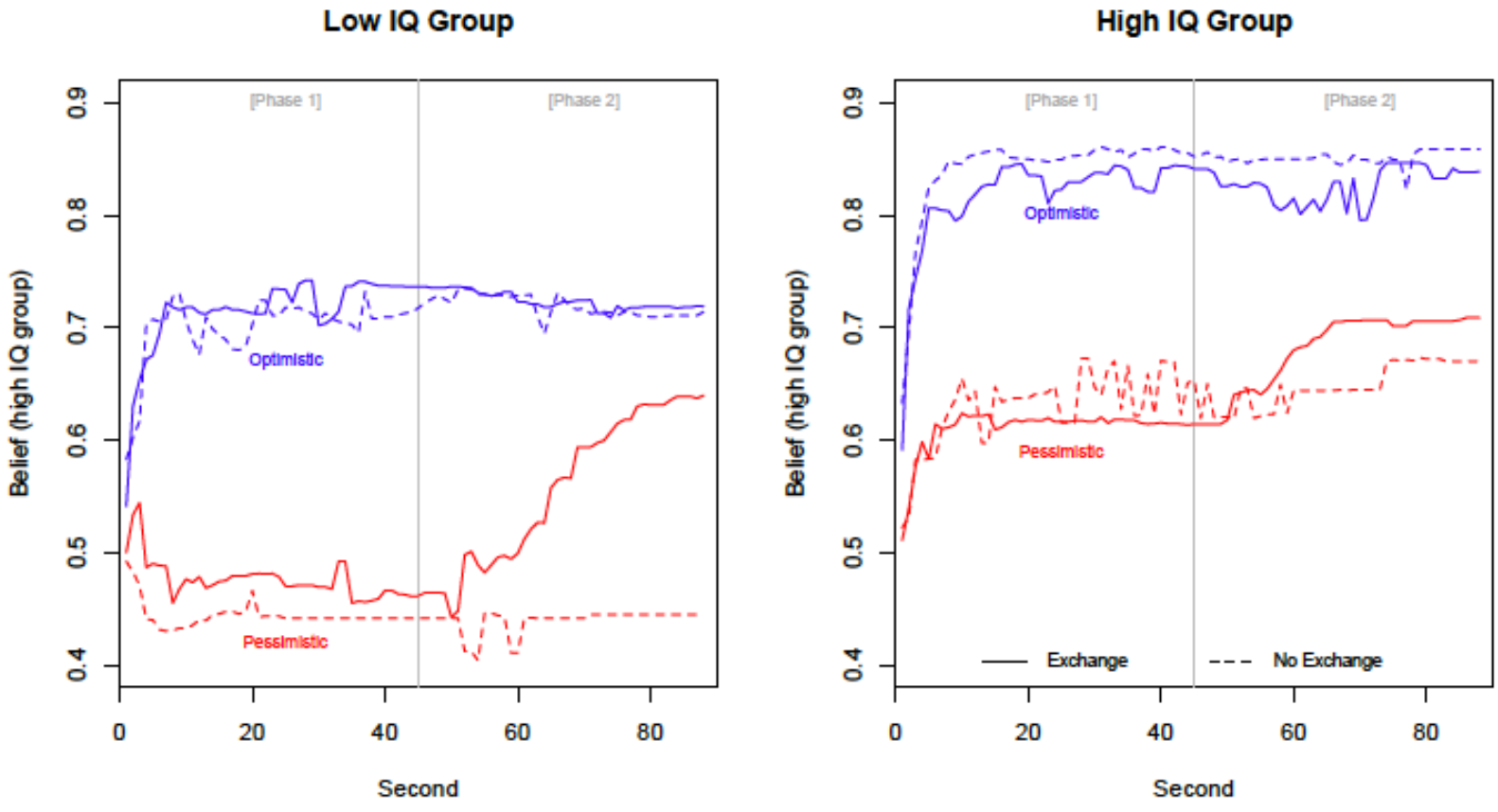
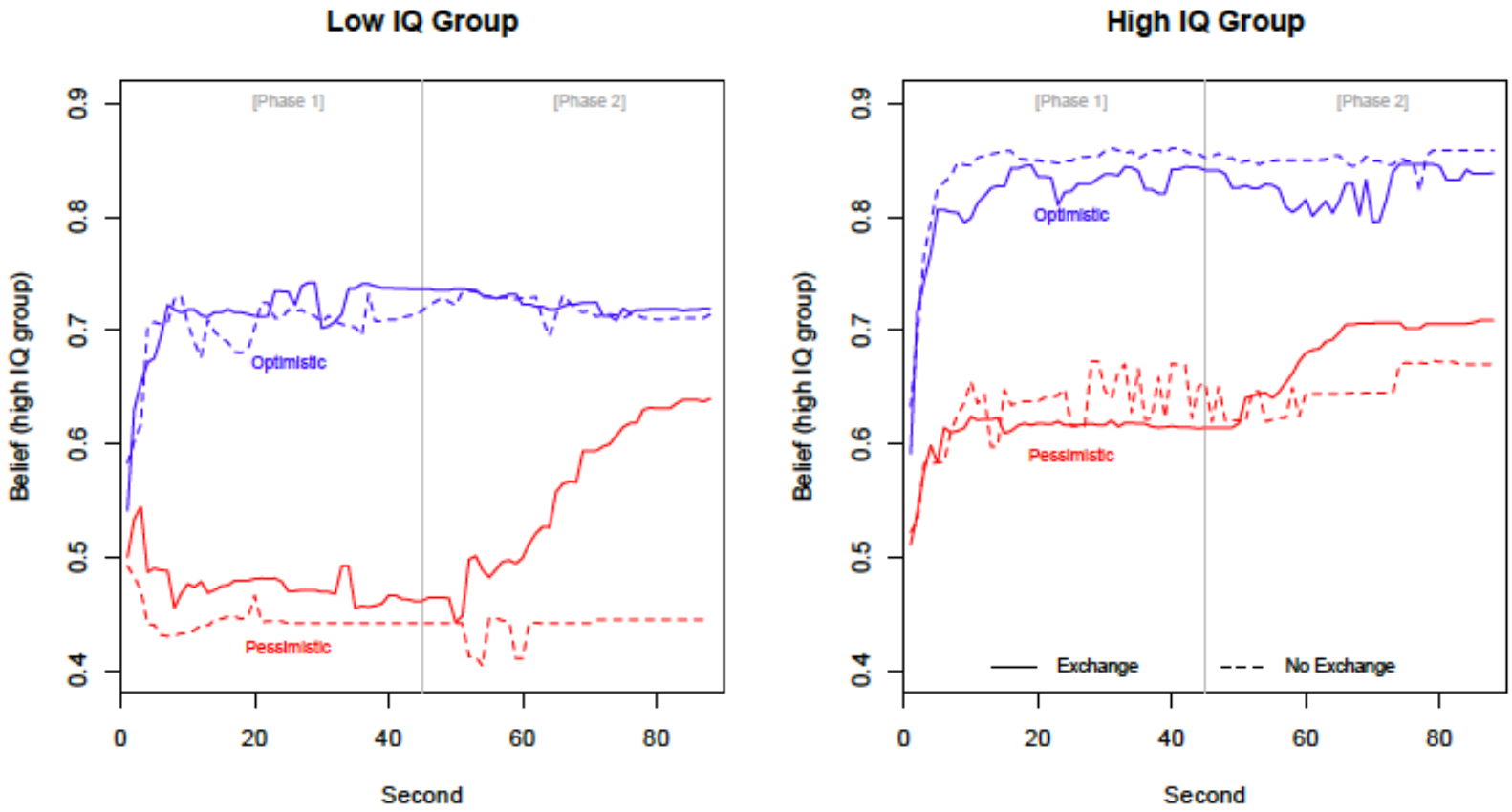
Results: Phase I



Result 1: Subjects' beliefs stabilize in phase 1 of the experiment. On average, subjects in the low IQ group hold upward biased initial beliefs about their assignment to the high IQ group. Beliefs in phase 1 are not statistically different between the Exchange and No Exchange treatment.

Results: Phase I



"subjects in the low IQ group believe, on average, incorrectly, that the likelihood that they are in the high IQ group is greater than 50% ($p < 0.01$)"

Results: Phase I

Table 7: OLS Estimation (Dependent Variable: Beliefs in Second 44)

	All	Low Group	High Group
Exchange	0.00310	0.0267	-0.0205
	(0.0381)	(0.0594)	(0.0407)
Constant	0.665***	0.577***	0.752***
	(0.0284)	(0.0430)	(0.0301)
Observations	160	80	80

Standard errors (clustered at the pair level) in parentheses.

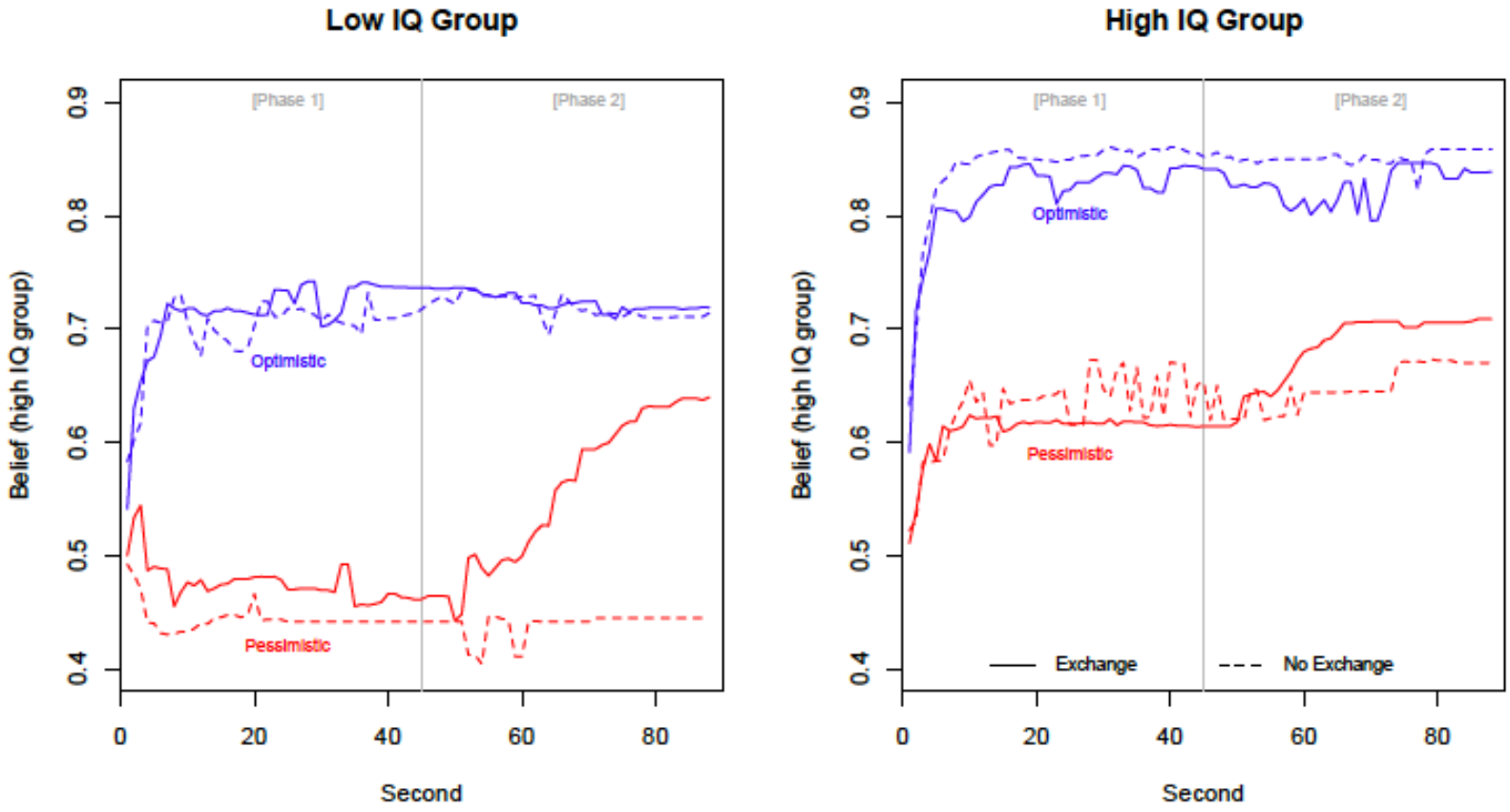
***1%, **5%, *10% significance.

Data from E-M and NE-M.

Exchange takes value 1 for E-M (0 otherwise).

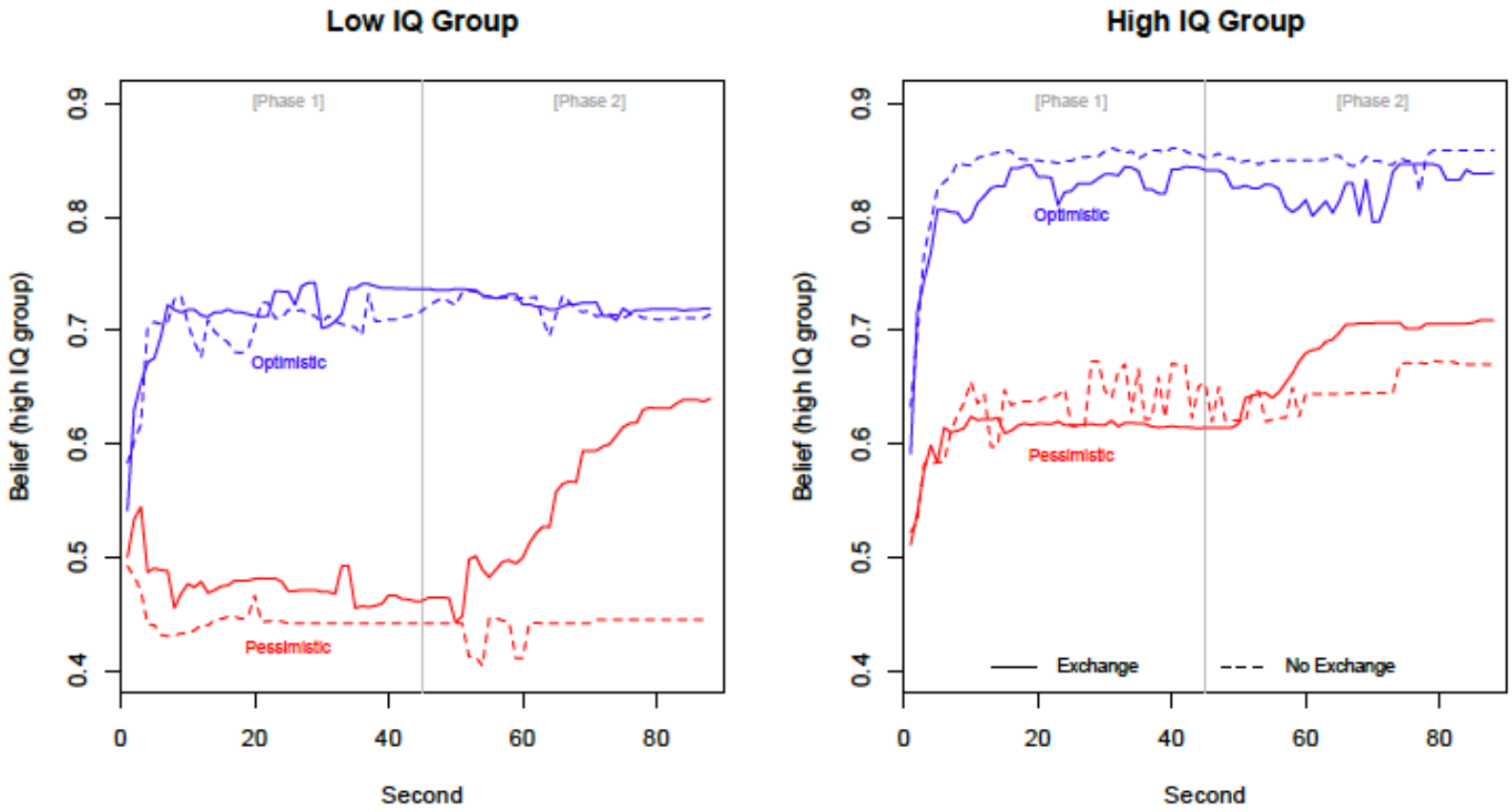
How should we think of belief bias in this setting?

Results: Phase II



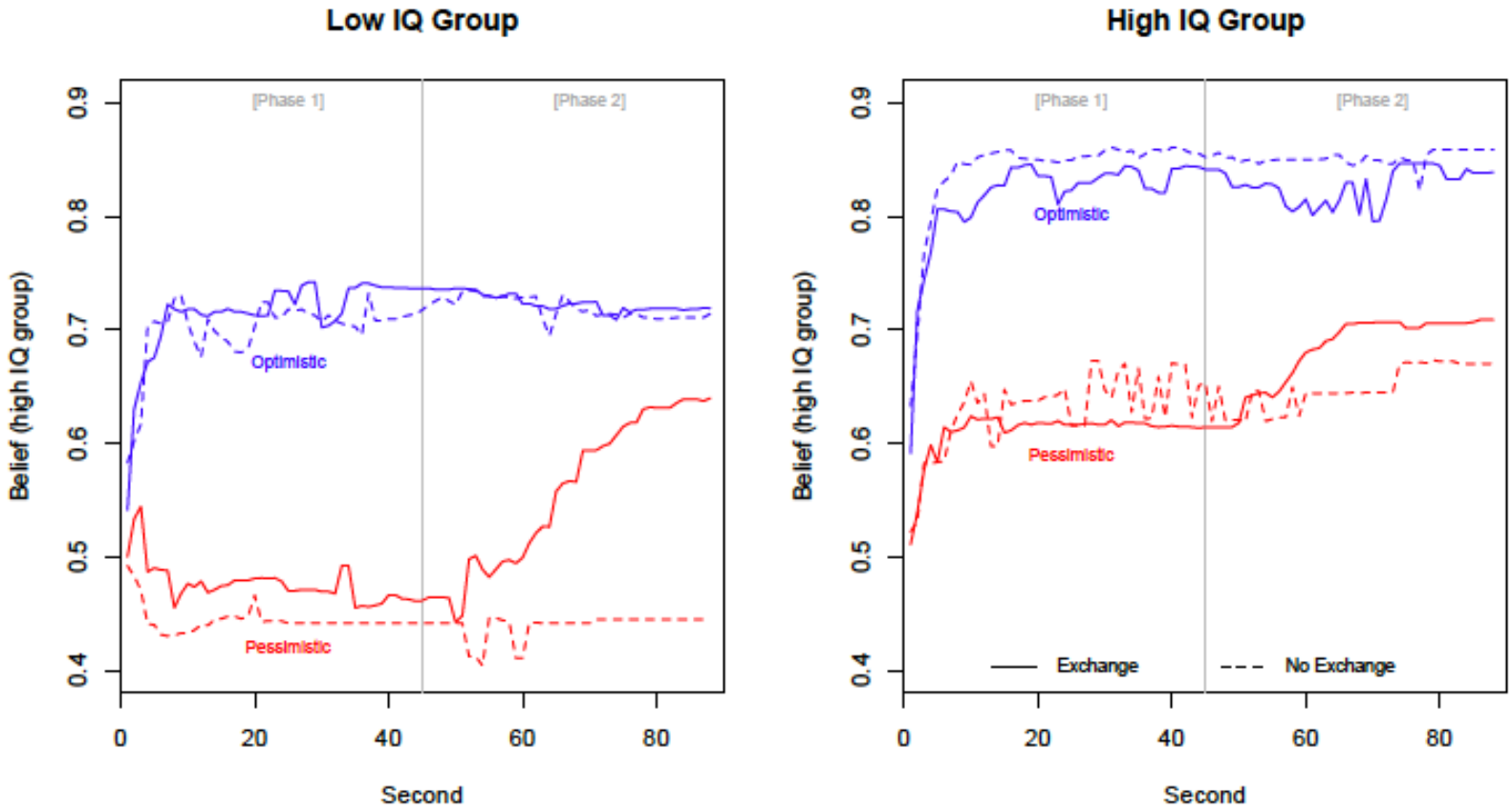
Result 2: Social exchange causes subjects' beliefs to partially converge but subjects show evidence of persistent disagreement.

Results: Phase II



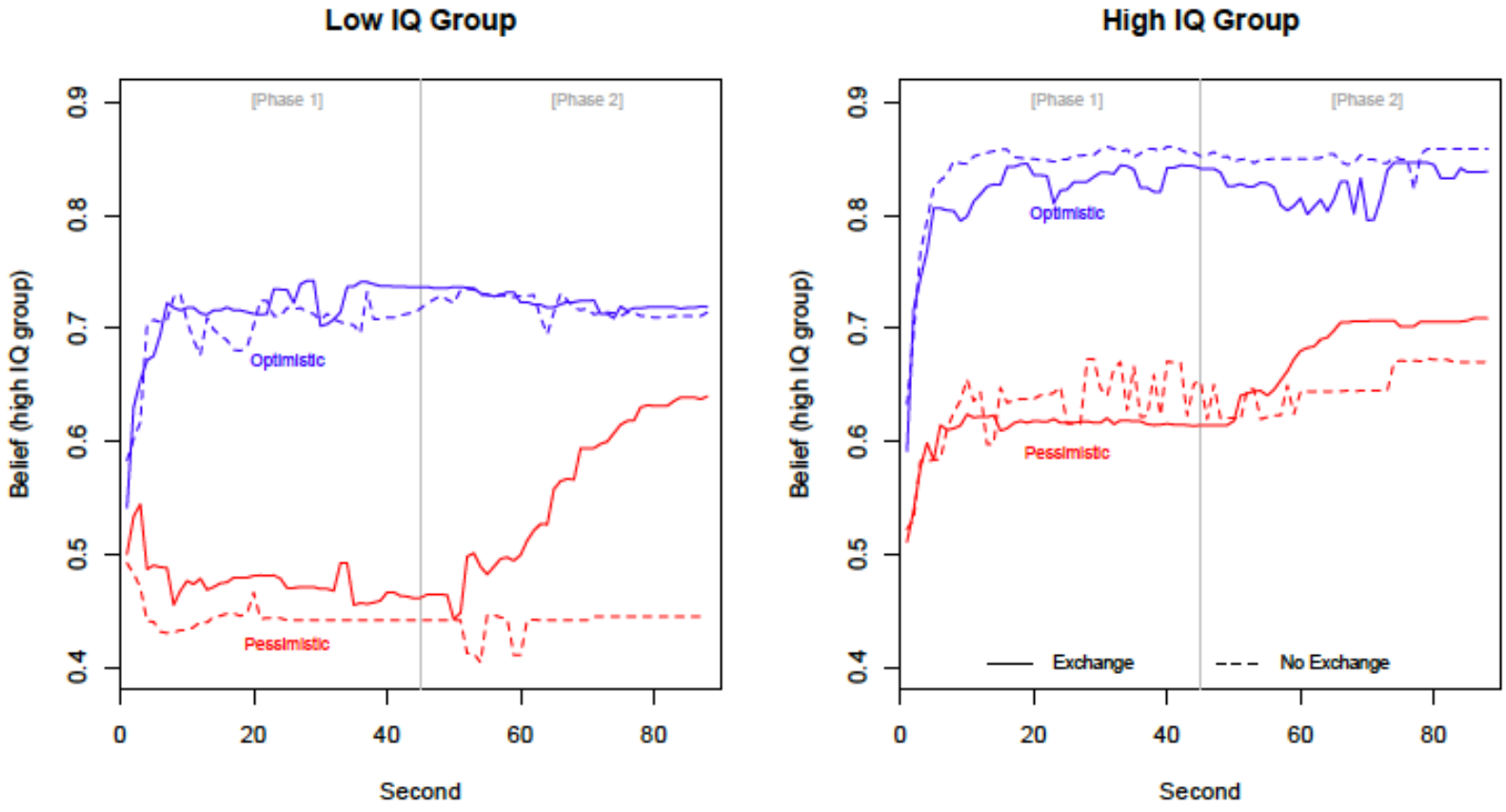
"Within a pair, the average absolute value difference between beliefs decrease by 14 percentage points ($p < 0.01$) from second 44 to second 89 in E-M."

Results: Phase II



"However convergence is not complete: on average the absolute difference between subjects' beliefs is 14 percentage points at the end of phase 2 (statistically different from zero with $p < 0.01$)"

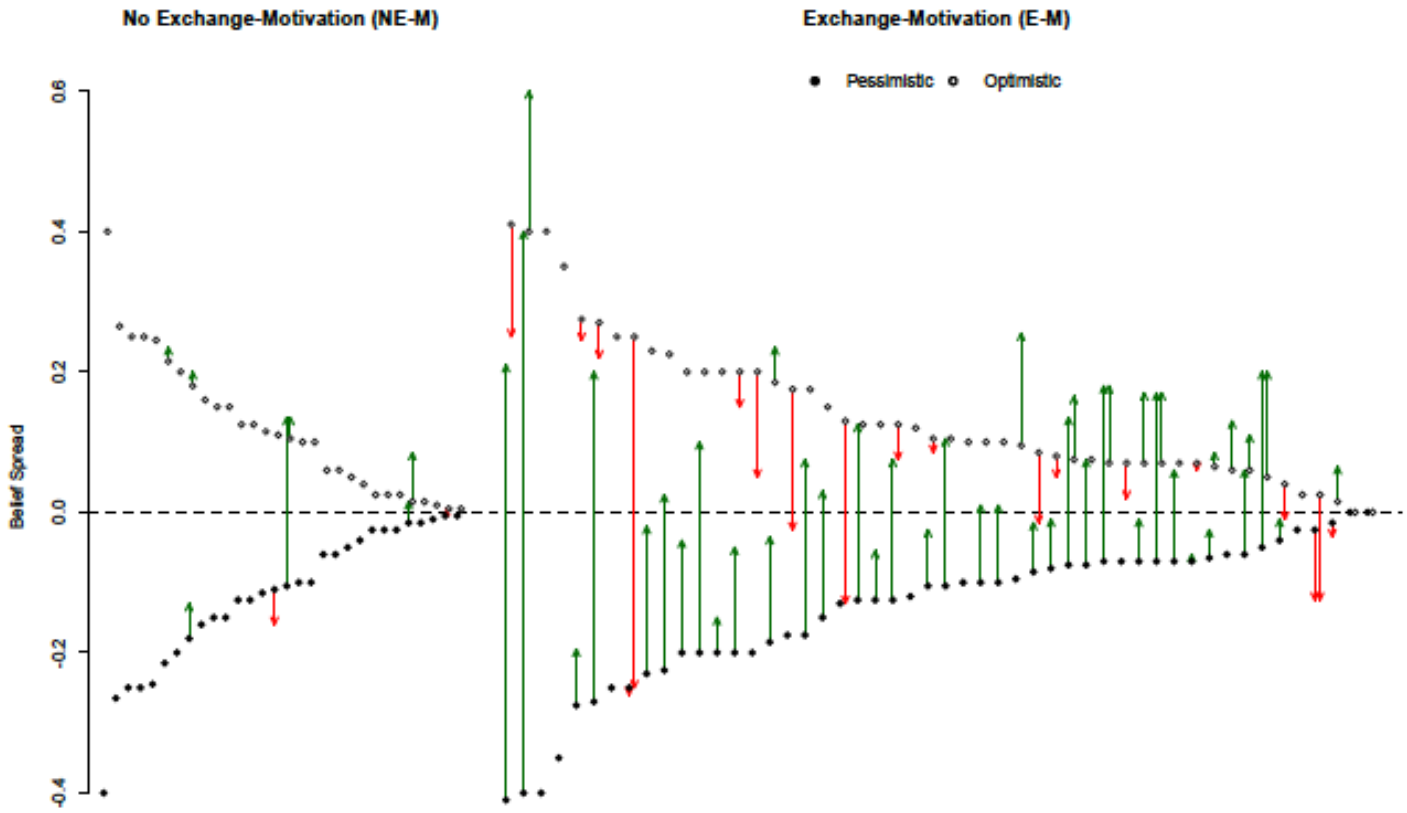
Results: Phase II



Result 3: Beliefs adjust systematically upwards as a result of social exchange, particularly for those in the low IQ group. Social exchange thus worsens bias on average. No similar effects occur in the absence of social interaction.

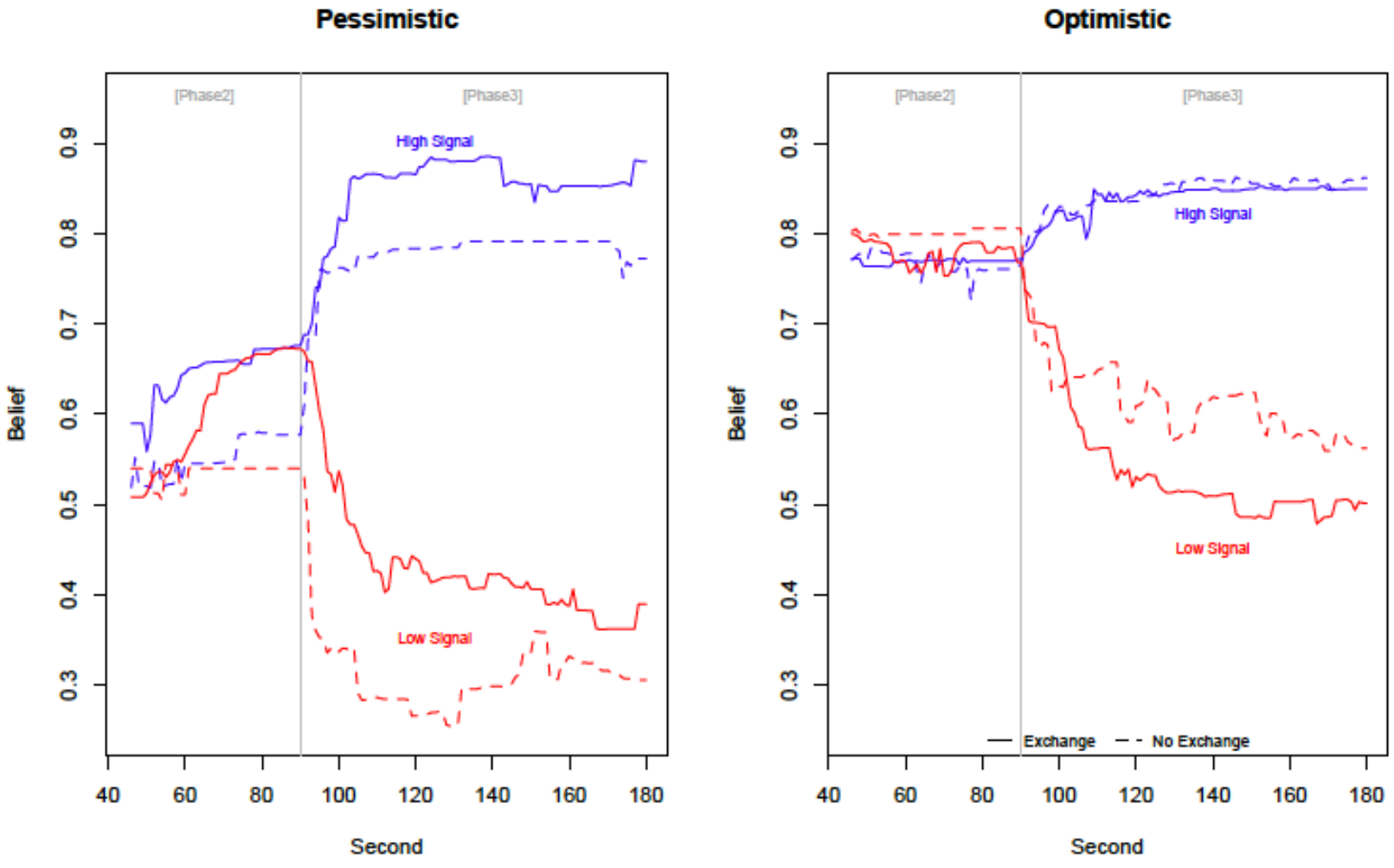
Results: Phase II

Second 44 beliefs and adjustments between end of phase 1 and end of phase 2:



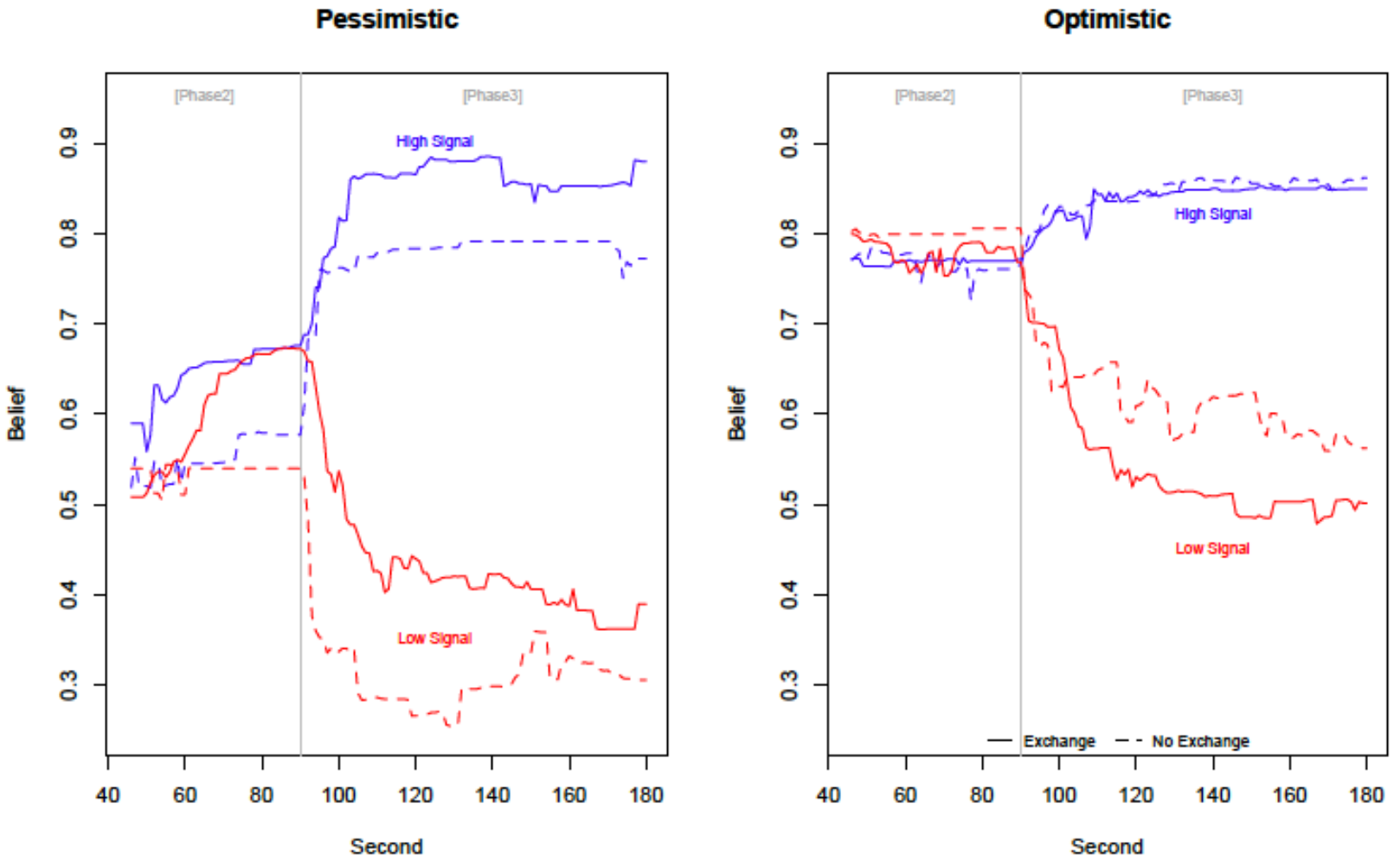
Result 4: The majority of pessimistic subjects adjust significantly upwards towards their more optimistic counterpart in Exchange-Motivation. By contrast only a minority of optimistic subjects adjust downwards towards their pessimistic counterpart (and almost as many adjust away from their pessimistic counterpart).

Results: Phase III



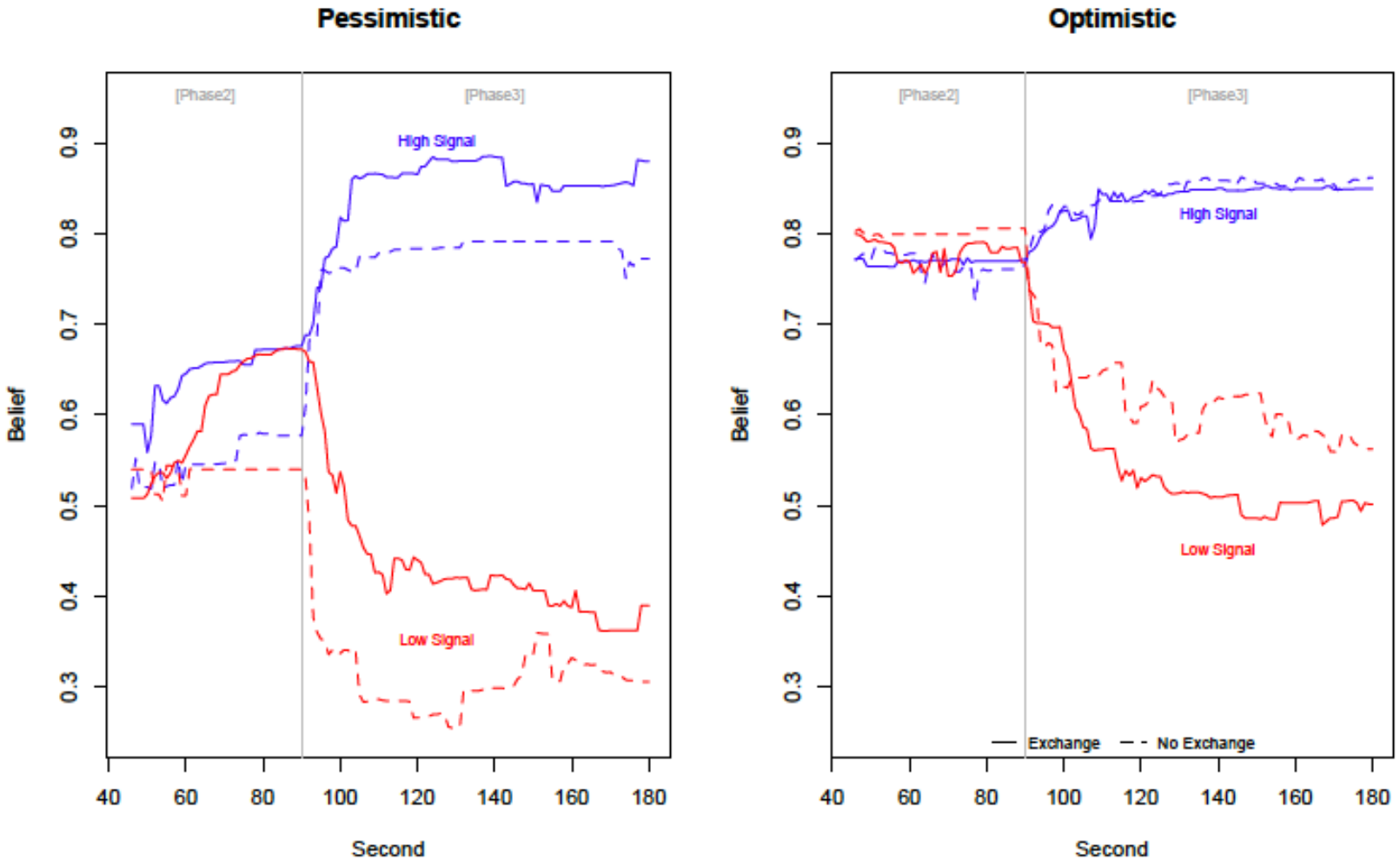
Result 5: Subjects respond strongly to public information.

Results: Phase III



Effect of signal in E-M: 41% **Effect of signal in NE-M:** 38%

Results: Phase III



Result 6: Public information mostly corrects for the amplification of bias generated by social exchange of beliefs. However, there is some evidence to suggest that social exchange may have persistent effects for some subjects.

The mechanism

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The mechanism

1. Others belief contain some information
2. Subjects don't know how much information they contain
3. And choose to interpret them in a way that fits their motivation
4. Different from confirmation bias because motivation and prior might go in opposite directions

Asymmetric updating

- Consider Part III
- p is belief at second 189
- p_0 is belief at second 89
- $s \in \{L, H\}$ is the signal

$$log\left(\frac{p}{1-p}\right) = \alpha log\left(\frac{p_0}{1-p_0}\right) + \beta log\left[\frac{P(s|H)}{P(s|L)}\right]$$

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$$log\left(\frac{p}{1-p}\right) = \alpha log\left(\frac{p_0}{1-p_0}\right) + \beta_h \mathbb{I}(s = h) log\left[\frac{P(H|H)}{P(H|L)}\right] + \beta_l \mathbb{I}(s = l) log\left[\frac{P(L|H)}{P(L|L)}\right]$$

Asymmetric updating

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- $s \in \{L, H\}$ is the signal
- $log\left(\frac{p}{1-p}\right) = \alpha log\left(\frac{p_0}{1-p_0}\right) + \beta log(\lambda_s)$

Updating in response to public signals

$$log\left(\frac{p}{1-p}\right) = \alpha log\left(\frac{p_0}{1-p_0}\right) + \beta_h \mathbb{I}(s = h) log(\lambda_h) + \beta_l \mathbb{I}(s = l) log(\lambda_l)$$

- p is belief at second 189
- p_0 is belief at second 89
- $\lambda_h = \frac{0.75}{1-0.75} = 3$
- $\lambda_l = 1/3$

Updating in response to public signals

	No-Exchange	Exchange
α	0.857***	0.798***
	(0.114)	(0.123)
β_h	0.999***	1.295***
	(0.191)	(0.325)
β_l	1.030***	1.254***
	(0.219)	(0.234)
Observations	60	100

Estimation results are on updating from end of phase 2 to 3.

Standard errors (clustered at the pair level) in parentheses.

***1%, **5%, *10% significance. Data from Motivation treatments.

Updating in response to social signals

- Consider Part II
- p is belief at second 89
- p_0 is belief at second 44
- $\tilde{p}$ = the other player's belief is the signal

$$log\left(\frac{p}{1-p}\right) = \alpha log\left(\frac{p_0}{1-p_0}\right) + \beta log\left[\frac{P(\tilde{p}|H)}{P(\tilde{p}|L)}\right]$$

Updating in response to social signals

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$$log\left(\frac{p}{1-p}\right) = \alpha log\left(\frac{p_0}{1-p_0}\right) + \beta log\left[\frac{P(\tilde{p}|H)}{P(\tilde{p}|L)}\right]$$

- **"Naive" benchmark:** $\frac{P(\tilde{p}|H)}{P(\tilde{p}|L)} = \frac{\tilde{p}}{1-\tilde{p}}$

Updating in response to social signals

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- $\tilde{p}$ = the other player's belief is the signal

$$log\left(\frac{p}{1-p}\right) = \alpha log\left(\frac{p_0}{1-p_0}\right) + \beta log\left[\frac{P(\tilde{p}|H)}{P(\tilde{p}|L)}\right]$$

- **"Naive" benchmark:** $\frac{P(\tilde{p}|H)}{P(\tilde{p}|L)} = \frac{\tilde{p}}{1-\tilde{p}}$
- "That is, if a subject's counterpart reports his belief of being in the high group as $\tilde{p}$, the subject considers this report to be generated with probability $\tilde{p}$ if they are in the high IQ group and $1-\tilde{p}$ if they are in the low IQ group."

Updating in response to social signals

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$$log\left(\frac{p}{1-p}\right) = \alpha log\left(\frac{p_0}{1-p_0}\right) + \beta log(\lambda_{\tilde{p}})$$

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$$log\left(\frac{p}{1-p}\right) = \alpha log\left(\frac{p_0}{1-p_0}\right) + \beta_h \mathbb{I}(\lambda_{\tilde{p}} > 1) log(\lambda_{\tilde{p}}) + \beta_l \mathbb{I}(\lambda_{\tilde{p}} \leq 1) log(\lambda_{\tilde{p}})$$

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Updating in response to social signals

	Sophisticated Benchmark		*Naive Benchmark*	
	Exchange	No-Exchange	Exchange	No-Exchange
α	0.721***	1.034***	0.773***	1.039***
	(0.117)	(0.0226)	(0.110)	(0.0219)
β_h	2.808***	0.212	0.363***	0.0290
	(0.693)	(0.261)	(0.0832)	(0.0359)
β_l	0.0655	0.0292	0.0334	0.0406
	(0.0776)	(0.0278)	(0.0589)	(0.0383)
Observations	100	60	100	60

Estimation results are on updating from end of phase 1 to 2.

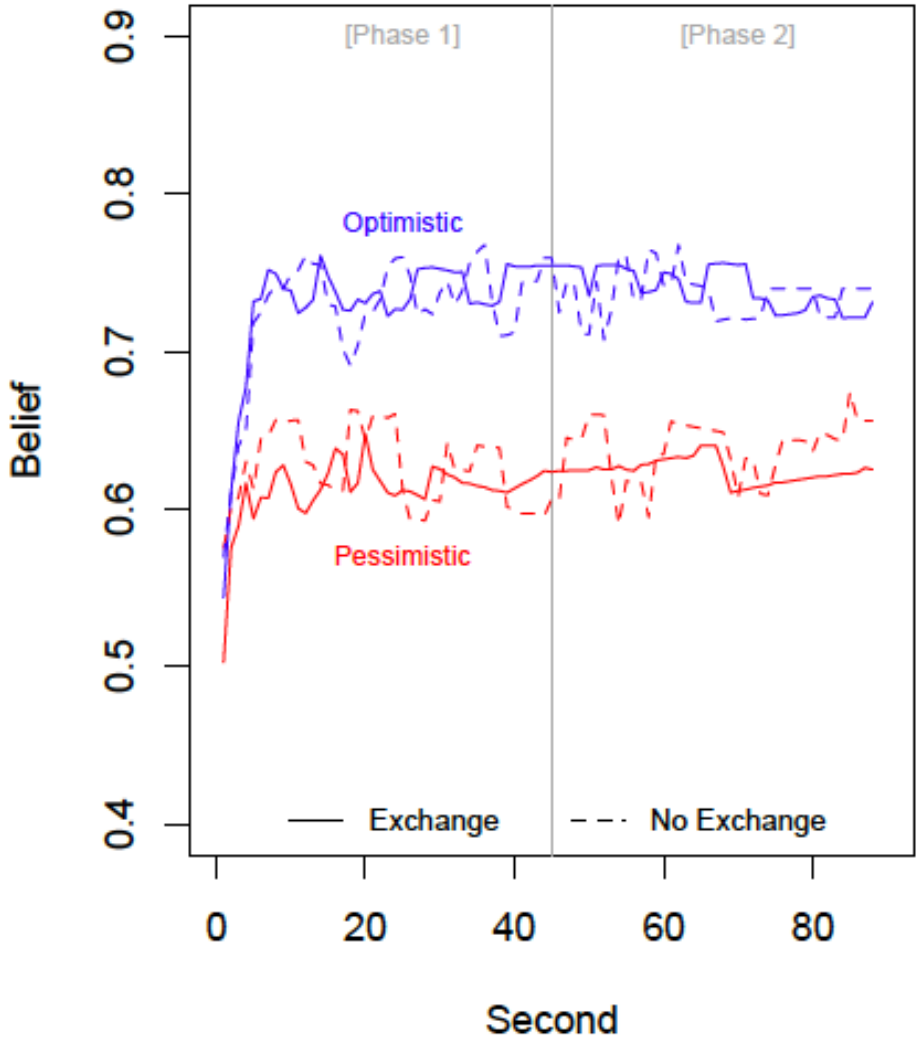
Standard errors (clustered at the pair level) in parentheses.

***1%, **5%, *10% significance. Data from Motivation treatments.

What drives the results?

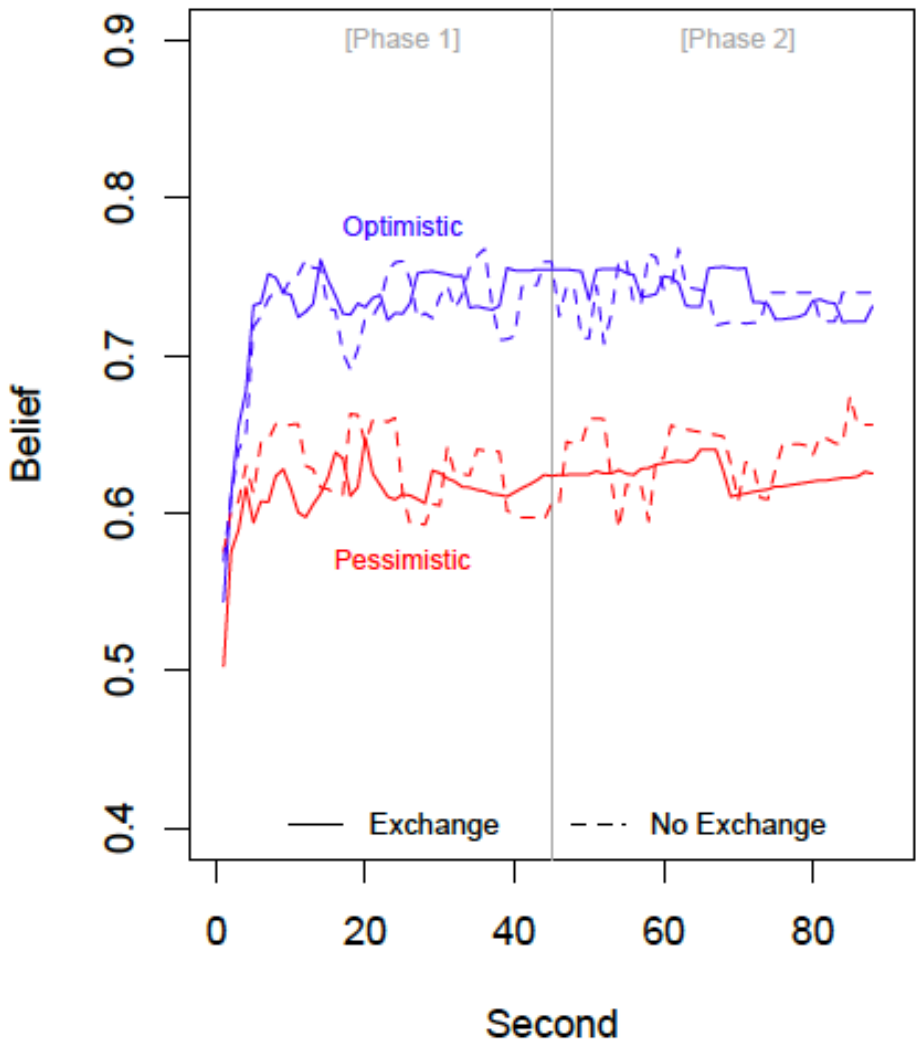
- Does "motivated reasoning" matter?
- Confirmation bias?

Exchange-No Motivation Task



Result 9: Social exchange does not have a significant effect on beliefs when there is no private information or scope for motivation.

Exchange-No Motivation Task



Should it? *"Note that in E-NM the prior associated with the likelihood of being in either group is exogenously determined and clearly communicated to the subjects" (p. 28)*

Confirmation bias

	Sophisticated Benchmark		*Naive Benchmark*	
	$p_0 < 0.5$	$p_0 > 0.5$	$p_0 < 0.5$	$p_0 > 0.5$
α	0.509	0.786***	0.526	0.873***
	(0.538)	(0.0842)	(0.588)	(0.0723)
β_h	3.476**	2.527***	1.036**	0.328***
	(1.380)	(0.554)	(0.403)	(0.0680)
β_l	0.543	0.0142	0.584	0.0221
	(0.487)	(0.0593)	(0.602)	(0.0479)
Observations	16	76	16	76

Estimation results are on updating from end of phase 1 to 2.

Standard errors (clustered at the pair level) in parentheses.

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Result 9: The asymmetric updating we observe in social exchange is not consistent with confirmation bias. Even those subjects with initially low priors respond more strongly to social signals that increase optimism (reinforce subject's motivation) relative to signals that decrease optimism (undermine subject's motivation).

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- To the extent that subjects want to make money, their motivated beliefs are correct beliefs
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- Is the Exchange-No Motivation treatment sufficient evidence that (intrinsically) motivated beliefs are necessary for the results?
- Try to think of an experiment that preserves the basic features of this one (including uncertainty about what your partner knows and what you know about the correct response) but removes the intrinsic motivation