Online Appendix for

"Individual and Collective Information Acquisition: An Experimental Study"

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Abstract

In this Online Appendix, we describe the details of the experimental interface and display sample instructions from our dynamic and static treatments. In addition, we offer several extensions to the underlying theoretical model and our data analysis. We illustrate the inconclusive effects of risk aversion in both static and dynamic setups. We then show that our risk and altruism elicitations have little explanatory power in our data. We inspect session effects and demonstrate that they are unlikely to generate our results. We also consider various levels of clustering in our analyses and offer additional observations pertaining to our static treatments.

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1 Interface

In what follows, we first describe several of our design choices and the workings of the experimental interface. We then offer two sample instructions, for our dynamic and static majority treatments.

1.1 Conveying Information

Given the information that unfolds (the evolution of the Brownian motion), we compute at every point in time the probability that choice A or choice B is correct and show this computation directly to participants. In doing so, we ensure that probabilities are adequately updated, and thus, none of our findings emerges as a direct consequence of participants' failure to compute Bayesian posteriors.

Figure 1: Information Bar

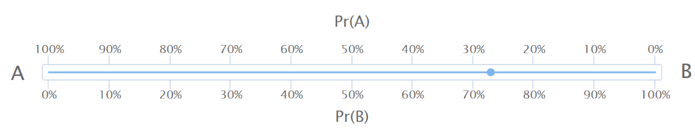
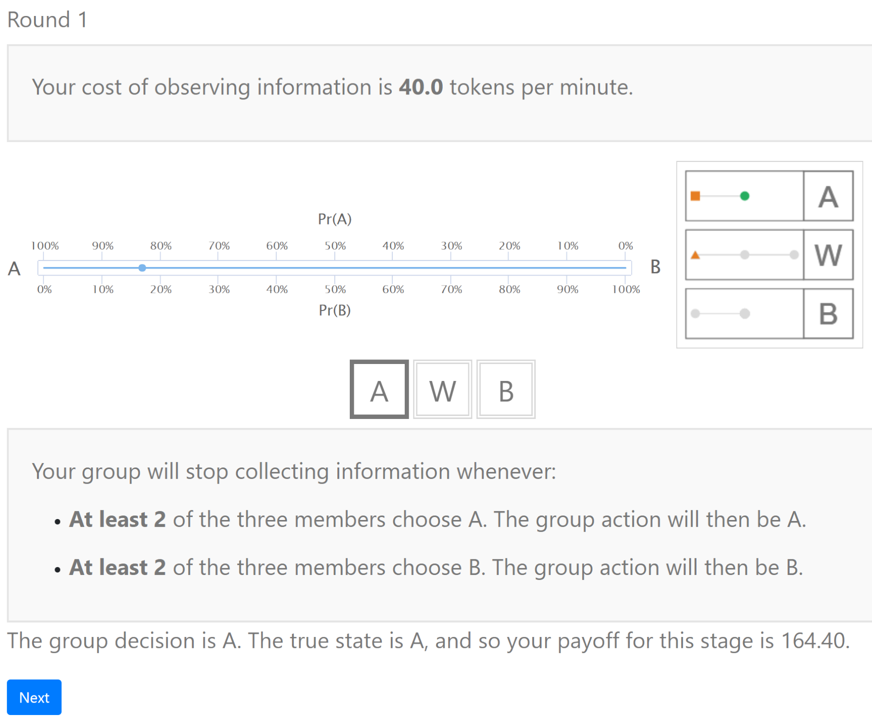


Figure 1 depicts the information bar through which participants are informed about the probability of choice A or choice B being correct. At the top, we depict the probability of choice A being correct, whereas, at the bottom, we depict $100 - P(A)$, or the probability that choice B is correct. At the beginning of each game, the blue dot (which in the figure is at 27% for A, or equivalently at 73% for B) is positioned exactly in the middle, indicating that initially the two choices are equally likely to be correct. As the Brownian motion evolves (which represents the log-likelihood of each state being correct), we transform it into a probability of choice A or choice B being correct. Namely we compute $P(A \,\text{is correct}) = \frac{e^{X_t}}{1+e^{X_t}}$ and accordingly position the blue dot.

1.2 Dynamic Treatment Interface

The interface seen by participants in the dynamic majority treatments is shown in Figure 2.

Figure 2: Dynamic Treatment Interface



- On the top left corner of the interface there is a round counter. This ranges from Round 1 all the way to Round 30.

- Below the round counter, throughout the experiment, participants are reminded of their waiting costs—their information acquisition costs. These costs are the same for all treatments, namely 40 tokens per minute.

- Below these reported costs, participants see the information bar described in Section 1.1.

- To the right of the information bar, participants have access to a panel that informs them of the decisions of other group members. Participants always see their own position as the green circle, and the choices of other group members as the orange square and triangle. As can be seen in Figure 2, both the participant as well as another group member have voted for A. An analogous panel appears for treatments involving groups using unanimity; it is absent in our individual treatments.

- Beneath the information bar, participants see an A (vote for A), W(wait), and B (vote for B) buttons. By clicking on these buttons, participants can submit/change their votes. Each round starts with the W button as the default choice. The current choice is highlighted using a gray frame around the corresponding button. In Figure 2, the participant has clicked on A.

- Beneath the voting buttons participants are once more reminded of the voting rule.

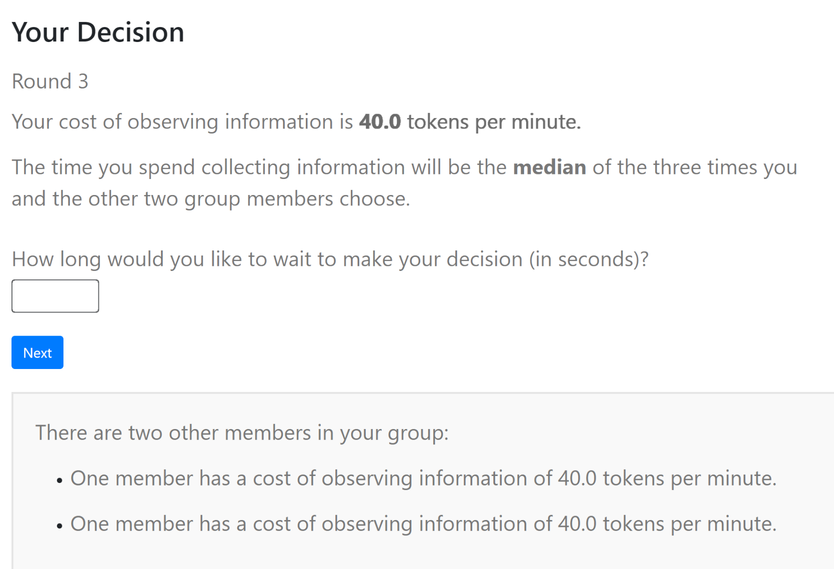
- Beneath the voting rule reminder, a new line appears after the pivotal vote is cast, informing the participants of the realized outcome, as well as their payoff. In the round depicted in Figure 2, the majority of participants chose option A, which matched the realized state, and their payoff was $200 - t \cdot 40 = 164.40$, where t represents the time group members took to arrive at the decision. Analogous reports occur for treatments in which groups use unanimity, or when individuals have full discretion.

- Whenever participants are ready, they can indicate their desire to start the new round by clicking the "Next" button. Once all participants within the session are ready, new random groups are formed and the new round begins.

1.3 Static Treatment Interface

The interface seen by participants in the static majority treatments is shown in Figure 3.

Figure 3: Static Treatment Interface



- In the top left corner of the interface there is a round counter. This ranges from Round 1 all the way to Round 30.

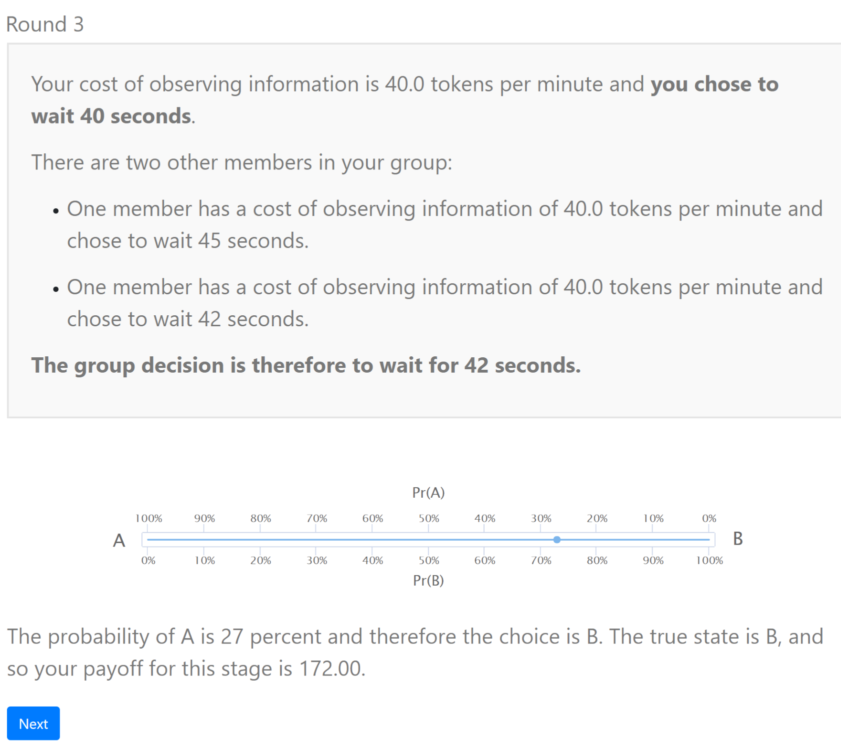
- Under the round counter, throughout the experiment, participants are reminded of their waiting costs (information acquisition costs). These costs are the same for all treatments, namely 40 tokens per minute. Furthermore, participants are also reminded of the voting rule.

- Below the information-cost information, there is a box in which participants can input their desired duration of information collection.

- Below the decision input, participants are reminded that other group members have the same waiting costs as they do.

Once all group members input their decisions, participants see the results page displayed in Figure 4. Here, participants watch the process evolve for the duration chosen by the pivotal voter.

Figure 4: Static Treatment Interface - Results



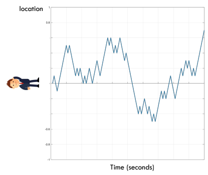
After the process evolves for the chosen duration, if the probability leans towards A(B), then A(B) is implemented as the group decision. Afterwards, participants are informed of the realized state, whether it matches their group decision, and of their payoff.

1.4 Sample Instructions

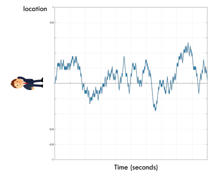
1.4.1 Initial Instructions

The initial instructions are identical for all treatments. Each treatment started with the instructions being read aloud, as well as two practice round for the participants to get used to the interface.

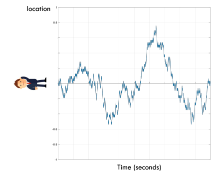
EVERY 0.01 SECOND



EVERY 0.002 SECOND

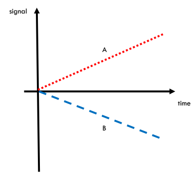


EVERY 0.001 SECOND

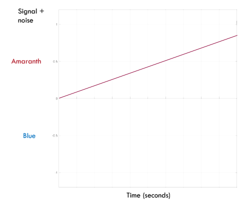


BACK TO INFORMATION YOU'LL SEE

- Recall the simple process we described: a signal that **increases 0.84 every minute if Jar A** (Amaranth) was chosen and **decreases 0.84 every minute if Jar B** (Blue) was chosen
- **We will now add the noise with vanishing time intervals to these curves**



EXAMPLE



INFORMATION: CONCLUSION

- Adding noise still allows you to learn over time: the higher the signal + noise, the more likely it is that A had been selected
- In fact, for every value of the signal + noise, a sophisticated statistician can translate what she sees into a probability that A had been selected
- Ultimately, that is what we will show you: the probability of A and B over time

1.4.2 Sample Instructions: Dynamic Majority Treatment

The examples of the process evolving were animated.

EXAMPLES

INFORMATION COSTS

- If your group correctly guesses the selected jar, you will receive **200 tokens**.
- However, with each passing minute you will lose **40 tokens** (**information costs**).

EXAMPLES 1

- Suppose your group guesses immediately that the jar is **A**.
- Your guess will be correct with 50% probability.
- You will not pay any costs.
- **Your overall expected payoff is: 0.5 x 200 – 0 = 100**

EXAMPLES 2

- Suppose your group guesses after 30 seconds, when the probability of Jar A selected is 70% .
- Your guess will be correct with 70% probability.
- You will pay 40 x ½ = 20 tokens for information.
- **Your overall expected payoff is: 0.7 x 200 – 20 = 120**

EXAMPLES 3

- Suppose your group guesses after one minute, when the probability of Jar A selected is 80% .
- Your guess will be correct with 80% probability.
- You will pay 40 x 1 = 40 tokens for information.
- **Your overall expected payoff is: 0.8 x 200 – 40 = 120**

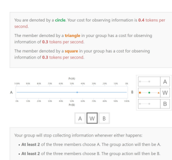
GROUP DECISION

- At the beginning of each round, you will be randomly grouped with two other individuals.
- The software will select the jar randomly, **A** and **B** equally likely.
- **Your group members change at random from round to round, as does the state.**

GROUP DECISION WITHIN A ROUND

- As long as a decision has not been made, you and your group members will see the same information.
- The costs of information will be **40 tokens per minute for each of you.**
- At any point in time, you can choose whether you would like to
  - Stop and guess **A**;
  - Stop and guess **B**;
  - Wait—choose **W**—and collect more information **at a cost of 40 tokens per minute.**
- You can change your mind as long as a decision has not been made.
- **You will be able to see what your group members are choosing throughout.**

INTERFACE



GROUP DECISION

- Once a majority in your group chooses either **A** or **B,** information collection will stop and that will be the group's decision:
  - If 2 or 3 members in your group choose **A,** your group's guess is **A**
  - If 2 or 3 members in your group choose **B,** your group's guess is **B**

Post-Experiment

- You will be paid the sum of your payoffs across **20 randomly selected rounds** (excluding the practice round).
- You will also be asked to complete several simple tasks at the end. You can earn additional money based on your decisions in these tasks.

Your Earnings

Your total earnings in the experiment are the sum of the following amounts:

- $10 show-up payment
- payoff from **20** out of 30 randomly selected real rounds:
  100 tokens = 1 dollar
- payoff from the simple tasks:
  100 tokens = 1 dollar

You need not tell any other participant how much you earned.

Let the Experiment Begin!

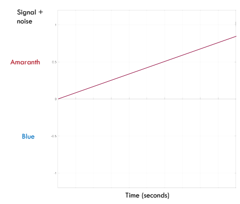
If there are no questions, we will now begin the actual experiment.

PEXL Princeton Experimental Laboratory for the Social Sciences

1.4.3 Sample Instructions: Static Majority Treatment

The examples of the process evolving were animated.

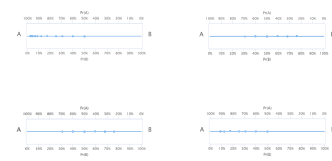
EXAMPLE



INFORMATION: CONCLUSION

- Adding noise still allows you to learn over time: the higher the signal + noise, the more likely it is that A had been selected
- In fact, for every value of the signal + noise, a sophisticated statistician can translate what she sees into a probability that A had been selected
- Ultimately, that is what we will show you: the probability of A and B over time

EXAMPLES

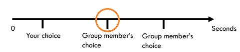


GROUP DECISION

- At the beginning of each round, you will be randomly grouped with two other individuals.
- The software will select the jar randomly, **A** and **B** equally likely.
- **Your group members change at random from round to round, as does the state.**

GROUP DECISION

- Each member of your group will select a desired waiting time for information.
- Your group's waiting time will be the **median** of the members' desired waiting times.



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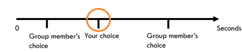

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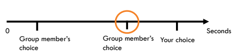

EXAMPLES

- Suppose you choose to wait 40 seconds and one of your group members chooses to wait 50 seconds, the other 60 seconds → your group will wait 50 seconds.
- Suppose you choose to wait 40 seconds and one of your group members chooses to wait 35 seconds, the other 60 seconds → your group will wait 40 seconds.

GROUP DECISION

- All members in your group will observe information evolving for the group's waiting time (the median of individual desired times).
- At the end of the group's waiting time, information will lean towards **A** or **B**.
- If the information leans towards **A**, the software will choose **A** as your group's guess.
- If the information leans towards **B**, the software will choose **B** as your group's guess.

INFORMATION COSTS

- If your group correctly guesses the selected jar, you will receive **200 tokens**.
- However, with each passing minute your group waits for information you will lose **40 tokens** (**information costs**).
- Thus, if your group correctly guesses the state after 45 seconds your payoff in that round will be:

  200-40 x (45/60) = **170 tokens.**
- If your group does not guess correctly, and the game ends after 45 seconds, your payoff in that round will be:

  0-40 x (45/60) = **-30 token.**

INFORMATION COSTS: MORE EXAMPLES

- If your group correctly guesses the jar after 30 seconds, your payoff in that round will be:

  200 – 40 x (30/60) = **180 tokens.**
- If your group does not guess correctly, and the game ends after 30 seconds, your payoff in that round will be:

  0 – 40 x (30/60) = **-20 tokens.**

INFORMATION COSTS: MORE EXAMPLES

- If your group chooses to wait 0 seconds, the probability you guess the jar correctly is 50%, so your expected payoff is

  0.5 x 200 – 40 x 0 = **100 tokens.**
- The longer you wait, the more likely you are to make a correct guess.
- **There is a tradeoff between getting things right and not spending too much.**

Post-Experiment

- You will be paid the sum of your payoffs across **20 randomly selected rounds** (excluding two practice rounds).
- You will also be asked to complete several simple tasks at the end. You can earn additional money based on your decisions in these tasks.

Your Earnings

Your total earnings in the experiment are the sum of the following amounts:

- $10 show-up payment
- payoff from **20** out of 30 randomly selected real rounds:
  100 tokens = 1 dollar
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You need not tell any other participant how much you earned.

Let the Experiment Begin!

If there are no questions, we will now begin the actual experiment.

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2 Beyond Risk Neutrality

2.1 Static Version

We use the setting and notation introduced in the section deriving our theoretical predictions in the main text.

Let $p(t) := \frac{1}{2}\left(\text{erf}\left(\frac{\sqrt{\mu t}}{2}\right)+1\right)$. The static optimization problem is then

$$\max_t \, p(t)u(x-ct) + (1-p(t))u(-ct).$$

Where x represents the reward, c represents the cost, t represents time the participant decides to wait, and $u(\cdot)$ is the utility function of the agent. The first-order condition yields

$$\frac{u(x-ct)-u(-ct)}{p(t)u'(x-ct)+(1-p(t))u'(-ct)}p'(t) = c.$$

Where $p'(t) = \frac{\mu e^{-\frac{1}{4}(\mu t)}}{4\sqrt{\pi}\sqrt{\mu t}}$. Given that $u(x-ct) = u(-ct) + \int_{-ct}^{x-ct} u'(s)ds$, the above can be written as

$$\frac{\int_{-ct}^{x-ct} u'(s)ds}{p(t)u'(x-ct)+(1-p(t))u'(-ct)}p'(t) = c.$$

Which reduces to $x\,p'(t) = c$ in the risk-neutral case. The multiplier of $p'(t)$ is not always lower or greater than one for any x, c, t. Thus, whether a risk-averse agent chooses to wait more or less than a risk-neutral agent is inconclusive. The following example illustrate the potential non-monotonicities of optimal information-collection duration times for agents with CRRA utilities.

Example (CRRA utilities) Consider an agent with a constant relative risk aversion (CRRA) utility. That is, let

$$u(z) = \frac{1}{1-\theta}z^{1-\theta} \qquad \theta > 0.$$

Since experimental payoffs are always positive, we focus on $z > 0$. Indeed, in the lab, agents receive a show-up fee of y in addition to their experimental payoffs. The expected utility can then be written as

$$\mathbb{E}\left[u(z)\right] = p(t)\left(\frac{1}{1-\theta}(x+y-ct)^{1-\theta}\right) + (1-p(t))\left(\frac{1}{1-\theta}(y-ct)^{1-\theta}\right).$$

The first-order condition yields

$$\frac{1}{4}\left(-2c\left(\mathrm{erf}\left(\frac{\sqrt{\mu t}}{2}\right)+1\right)(-ct+x+y)^{-\theta} - 2\mathrm{cerfc}\left(\frac{\sqrt{\mu t}}{2}\right)(y-ct)^{-\theta}\right)$$
$$+\frac{1}{4}\left(+\frac{\mu e^{-\frac{1}{4}(\mu t)}(-ct+x+y)^{1-\theta}}{\sqrt{\pi}(1-\theta)\sqrt{\mu t}} + \frac{\mu e^{-\frac{1}{4}(\mu t)}(y-ct)^{1-\theta}}{\sqrt{\pi}(\theta-1)\sqrt{\mu t}}\right) = 0.$$

If $\theta = 0$, the optimal duration t is that described in the main text—for $x = 1$, $c = 0.2$ and $\mu = 1.4$, we have $t^* = 0.49$. For any value of $\theta \neq 0$, there is no closed-form solution for the optimal information-collection duration. Let $y = 0.3$, allowing for $t \in [0, 1.5]$ without introducing a negative payoff in any state. We numerically find that the optimal waiting time with $\theta = 0.2$ is $t^* = 0.51$, while with $\theta = 0.8$, the optimal waiting time is $t^* = 0.46$. Thus, the optimal information-collection duration responds non-monotonically to risk aversion.

Why can risk aversion have such non-monotonic effects on the optimal duration? Intuitively, to reduce uncertainty, agents have to wait longer. However, waiting longer shift payoffs downward, since waiting is costly. Greater risk aversion might make it beneficial to decrease payoffs in both states for the sake of more certainty. There is a countervailing force, however: with greater risk aversion, a larger waiting cost may be particularly painful when the ultimate guess is incorrect. How these two forces balance one another depends on the utility function.

2.2 Dynamic Version

Consider the individual dynamic case. Suppose an agent uses a threshold posterior of $\tilde{p}$. This threshold gives rise to a distribution of end times, $f(t|\tilde{p})$ (for which only a Fourier series representation can be constructed). For any $\hat{t}$ at which information-collection terminates, the agent receives the following lottery

$$\tilde{p}u(x - c\hat{t}) + (1-\tilde{p})u(-c\hat{t}).$$

The agent would be choosing the optimal $\tilde{p}$ to maximize her expected utility

$$\max_{\tilde{p}\in[0.5,1]} \int_0^\infty \left(\tilde{p}u(x-cs)+(1-\tilde{p})u(-cs)\right) f(s|\tilde{p})ds.$$

By choosing a larger $\tilde{p}$ the agent minimizes the uncertainty in the lottery she receives. However, this increases the uncertainty regarding the time it takes to reach a decision. The effects of risk are, again, unclear.

Below, we use our risk elicitations to illustrates that risk, indeed, has limited explanatory power in our data.

3 Dynamic Treatments: Additional Analysis

3.1 Observed and Simulated Dynamic Treatment Groups

In addition to the cumulative distribution plots and the Kolmogorov-Smirnov tests appearing in the main text, below we present regressions in which we estimate the mean posterior of the observed and simulated group treatments. Concretely, in Table 1, d_{Sim} is a dummy variable equal to 0 for observed data points, and 1 for simulated data points. The constant captures the mean posterior in the observed data, whereas the coefficient of d_{Sim} captures the difference in mean posteriors between the observed and simulated data. We cluster errors at the individual level.

Table 1: Observed and Simulated Dynamic Treatment Groups

	Posterior	
	Majority	Unanimity
d_{Sim}	0.0477***	0.000878
	(0.00847)	(0.00756)
Constant	0.727***	0.818***
	(0.00678)	(0.00454)
N	330480	330480

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

In line with the conclusions drawn in the main text, decision posteriors in the dynamic majority treatment are significantly lower than those derived from simulated groups of individuals using majority rule. In contrast, decision posteriors in the dynamic unanimity treatment are not significantly different than those derived from simulated groups of individuals using unanimity.

3.2 Voting Probabilities in the Last 15 Rounds

Table 2 replicates the analysis of individual voting probabilities reported in the text, restricting attention to the last 15 rounds of sessions. The results are qualitatively similar to those pertaining to data from all rounds, albeit less significant due to the reduction in power.

Table 2: Probit Regression: Last 15 Rounds

	$P(Vote)$					
	Individual	Majority	Unanimity	Individual	Majority	Unanimity
Posterior	5.421***	5.057***	5.779***	5.541***	3.826***	5.793***
	(0.524)	(0.495)	(0.520)	(0.601)	(0.605)	(0.557)
Time	0.218*	0.711***	0.396***	0.330***	0.611***	0.410***
	(0.128)	(0.179)	(0.121)	(0.122)	(0.191)	(0.118)
Slope				0.123**	0.107**	0.0223
				(0.0541)	(0.0463)	(0.0373)
Standard Dev				-0.265	0.989***	-0.122
				(0.437)	(0.379)	(0.345)
Constant	-5.138***	-4.604***	-5.507***	-5.361***	-4.007***	-5.521***
	(0.464)	(0.342)	(0.424)	(0.531)	(0.451)	(0.466)
N	4335	3553	6201	3810	2822	5474

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

3.3 Risk Aversion, Altruism, and Alternative Clustering

In this section, we analyze alternative specifications for the analysis of our dynamic treatment data. The first column in Table 3 reports results from regressions focused on our main treatment effects in which standard errors are clustered at the individual level. The regressions include controls for risk attitudes and altruism, through two new explanatory variables: *Tokens Sent* and *Tokens Not Invested*. As mentioned in our description of the experimental design, at the end of each session, participants completed two risk-elicitation tasks as in Gneezy and Potters (1997). Namely, participants had 200 tokens to invest in a safe or risky asset. Tokens that were not invested were kept in the safe asset. The variable *Tokens Not Invested*, which can take values between 0 and 200, represents the amount participants decided to keep in the safe asset (and not invest in the risky asset).[1] Roughly speaking, the higher this value, the more risk averse participants are. At the end of each session, participants also played a dictator game, in which they were given 200 tokens and decided how much to keep for themselves, and how much to give to another, randomly-paired participant. The variable *Tokens Sent* represents the amount of tokens participants gave.[2] Since we

[1] In the majority and unanimity treatments, this variable represents the group average tokens not invested.

[2] In the majority and unanimity treatments, this variable represents the group average tokens sent.

elicit each measure twice, we can run an instrumental-variable regression, using the first elicitation as an instrument for the second. Doing so accounts for the fact that these are noisy elicitations, see Gillen et al. (2019).

Table 3: Dynamic Treatments - Alternative Specifications

	Posterior						
	Individual Level Clustering	No Clustering			Process Level Level Clustering		
	All Rounds	All Rounds		Last 15 Rounds	All Rounds		Last 15 Rounds
Constant	0.744***	0.767***	0.755***	0.744***	0.767***	0.755***	0.744***
	(0.0371)	(0.00293)	(0.00411)	(0.00993)	(0.0119)	(0.0135)	(0.0123)
d_M	-0.0329**	-0.0404***	-0.0362***	-0.0329***	-0.0404***	-0.0362***	-0.0329***
	(0.0134)	(0.00519)	(0.00727)	(0.00738)	(0.00539)	(0.00688)	(0.00640)
d_U	0.0453***	0.0508***	0.0444***	0.0453***	0.0508***	0.0444***	0.0453***
	(0.0141)	(0.00519)	(0.00727)	(0.00750)	(0.00469)	(0.00468)	(0.00432)
Last 15 I	0.0247***		0.0247***	0.0247***		0.0247***	0.0247***
	(0.00643)		(0.00581)	(0.00582)		(0.00768)	(0.00741)
Last 15 M	0.0162***		0.0162*	0.0162*		0.0162***	0.0162***
	(0.00614)		(0.00847)	(0.00849)		(0.00467)	(0.00450)
Last 15 U	0.0376***		0.0376***	0.0376***		0.0376***	0.0376***
	(0.00665)		(0.00847)	(0.00849)		(0.00958)	(0.00924)
Tokens Sent	0.000252			0.000252**			0.000252***
	(0.000212)			(0.000106)			(0.0000656)
Tokens Not Invested	0.0000434			0.0000434			0.0000434
	(0.000307)			(0.0000904)			(0.0000463)
N	1980	1980	1980	1980	1980	1980	1980

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

The coefficients of neither *Tokens Sent*, nor *Tokens Not Invested*, appear statistically significant. The sign and magnitude of all other estimated parameters remains roughly unchanged.

The following three columns in Table 3 report results from analogous regressions with and without *Tokens Sent* and *Tokens Not Invested*. In these regressions, standard errors are not clustered. The last three columns in Table 3 report results from the same analysis with standard errors clustered at the process level. Recall that our experimental design entails a draw of 15 Wiener processes, each utilized twice.[3] It is at this process level that we cluster in the last three columns.

Results are similar across all these specifications. One exception is the coefficient on our altruism proxy, *Tokens Sent*, which appears statistically significant, if very small, when we do not cluster standard errors or cluster at the process level. Nonetheless, about 60% of participants give 0 tokens, and more than 80% give less than 50 tokens. Given the estimated parameter value, this variable has limited ability to explain the variations in stopping posteriors we observe.

The regression results presented in the Appendix of the main text entailed individual-level clustering of standard errors. Table 4 presents analogous regression results with no clustering and process-level clustering. The first two columns consider process-level clustering at the group level.

[3] In each session, the last 15 processes corresponded to a reflection of the first 15. Therefore, we effectively have two observations for each process in each of our treatments.

The next columns focus on individual stopping posteriors, as those discussed in the main text. The fixed-effects regression cannot be presented with process-level clustering as the panels are not nested within clusters.

Table 4: Decreasing Thresholds - Alternative Clustering

	Posterior					
	Process Level Clustering		No Clustering			
	OLS Regression		Ordinary Regression		Fixed Effects Regression	
	All Rounds	Last 15 Rounds	All Rounds	Last 15 Rounds	All Rounds	Last 15 Rounds
Constant	0.785***	0.806***	0.785***	0.806***	0.777***	0.821***
	(0.00929)	(0.00912)	(0.00463)	(0.00542)	(0.00426)	(0.00585)
d_M	-0.0303***	-0.0372***	-0.0303***	-0.0372***		
	(0.00973)	(0.0109)	(0.00819)	(0.00958)		
d_U	0.0347***	0.0431***	0.0347***	0.0431***		
	(0.00521)	(0.00677)	(0.00819)	(0.00958)		
Last 15 I	0.0247***		0.0247***		0.0299***	
	(0.00768)		(0.00546)		(0.00521)	
Last 15 M	0.0162***		0.0162**		0.0218***	
	(0.00467)		(0.00796)		(0.00775)	
Last 15 U	0.0376***		0.0376***		0.0431***	
	(0.00958)		(0.00796)		(0.00794)	
Slow I	-0.0648***	-0.0576***	-0.0648***	-0.0576***		
	(0.0171)	(0.0177)	(0.00547)	(0.00793)		
Slow M	-0.0774***	-0.0736***	-0.0774***	-0.0736***		
	(0.0160)	(0.0170)	(0.00798)	(0.0116)		
Slow U	-0.0440*	-0.0271	-0.0440***	-0.0271**		
	(0.0217)	(0.0227)	(0.00798)	(0.0116)		
Time I					-0.000651***	-0.00110***
					(0.000149)	(0.000180)
Time M					-0.00133***	-0.00167***
					(0.000397)	(0.000553)
Time U					-0.000517***	-0.000700***
					(0.000184)	(0.000240)
N	1980	990	1980	990	1980	990

Standard errors in parentheses

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

The only noticeable difference from the results presented in the Appendix of the main text is the weakening, or loss of statistical significance, of *Slow U* under process-level clustering.

3.4 Session Effects

Since our group treatments entail a limited number of sessions, one may worry that interactions within sessions are driving our results. We now illustrate various ways by which our results appear robust to the session-partitioning in our data.

3.4.1 Probit with Session-Level Clustering

Our results remain statistically significant even when clustering standard errors at the session level, as shown in Table 5 here. The table presents estimates from analysis analogous to that underlying Table 3 of the main text. As can be seen, results are virtually identical.

Table 5: Probit Regression (Session-level Clustering)

	$P(Vote)$					
	Individual	Majority	Unanimity	Individual	Majority	Unanimity
Posterior	5.357***	5.149***	5.690***	5.071***	3.787***	5.463***
	(0.375)	(0.813)	(0.0938)	(0.178)	(0.605)	(0.0388)
Time	0.242***	0.798***	0.333***	0.313***	0.673**	0.328***
	(0.0840)	(0.134)	(0.111)	(0.0666)	(0.279)	(0.125)
Slope				0.137***	0.132***	0.0475***
				(0.0179)	(0.0223)	(0.00877)
Standard Dev				-0.142	0.626***	0.350***
				(0.317)	(0.173)	(0.0592)
Constant	-4.980***	-4.626***	-5.263***	-4.891***	-3.880***	-5.192***
	(0.251)	(0.394)	(0.0460)	(0.112)	(0.316)	(0.0862)
N	7865	6772	11113	6824	5301	9660

Standard errors in parentheses
Session-level clustering
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We next show that there is a statistically significant difference between the estimated parameters across treatments. Table 6 reports regression results that speak explicitly to the difference between the estimated parameters for the majority and unanimity treatments, clustering at the session level. Instead of running the regressions separately, we define D_M as a dummy variable that equals 1 for observations from the majority treatment and 0 otherwise. We interact this dummy variable with all parameters of interest. Thus, for all intents and purposes, the regressions whose results are reported in Table 6 are nearly identical to those underlying Table 5 here. However, Table 6 allows direct conclusions on the statistical significance of differences between the treatments.

Table 6: Unanimity vs Majority (Session-level Clustering)

	$P(Vote)$	
Posterior	5.690***	5.463***
	(0.0861)	(0.0357)
Time	0.333***	0.328***
	(0.102)	(0.115)
Slope		0.0475***
		(0.00805)
Standard Dev		0.350***
		(0.0543)
Constant	-5.263***	-5.192***
	(0.0422)	(0.0792)
Posterior $\times D_M$	-0.540	-1.677***
	(0.776)	(0.575)
Time $\times D_M$	0.465***	0.345
	(0.163)	(0.289)
Slope $\times D_M$		0.0842***
		(0.0227)
Standard Dev $\times D_M$		0.276
		(0.173)
D_2	0.638*	1.313***
	(0.376)	(0.310)
N	17885	14961

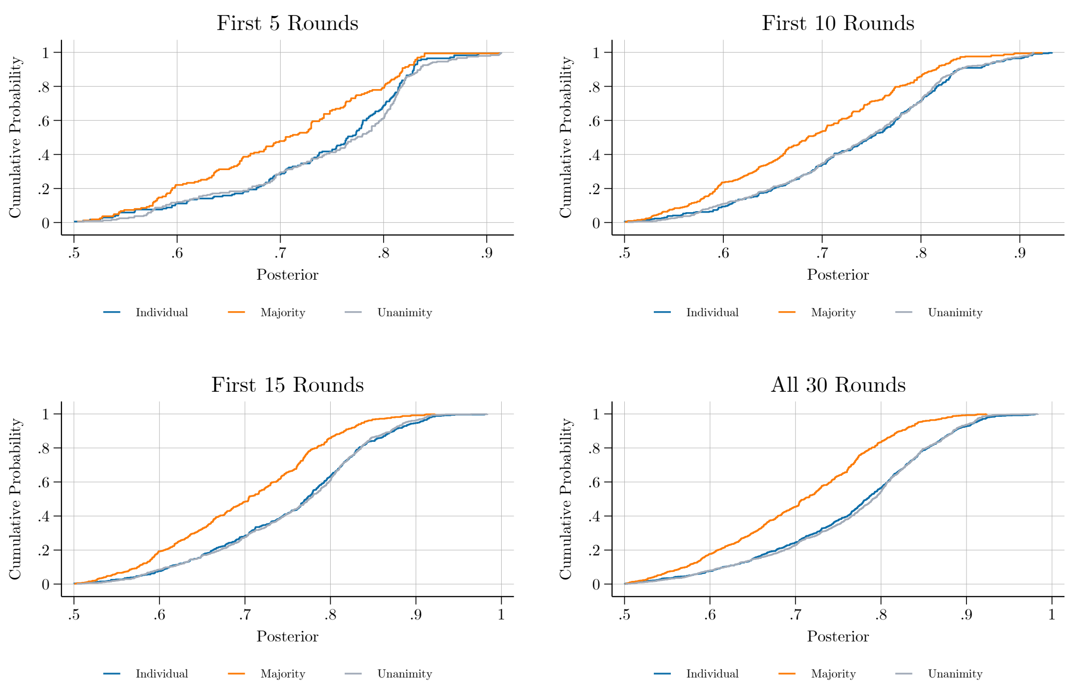
Standard errors in parentheses
Session-level clustering
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As can be seen, when regressing $P(Vote)$ on posteriors and time, the majority treatment exhibits significantly more pronounced reactions to time than the unanimity treatment. When regressing $P(Vote)$ on the posterior, time, slope, and standard deviation of the process, we see that results from the majority treatment significantly differ from those under the unanimity treatment in the initial intercept, the reaction to the posterior, as well as the reaction to the slope of the process. In all cases, we have p-values lower than 0.01. Similar differences can be seen for the individual and majority treatments.

3.4.2 Presence of Effects in Initial Rounds

The effects we capture are present from the very start of our sessions, before individuals have had a chance to interact extensively with others in the session, as shown in Figure 5. The figure shows that the comparisons across treatments is present in the first 5, first 10, first 15, as well as in all 30 rounds.

Figure 5: Effect Present in Initial Rounds in Dynamic Treatments



Across all our treatments, the distributions of pivotal choices similarly exhibit striking stability over time.

Table 7 establishes statistical significance of the comparisons depicted for early rounds in Figure 5. We utilize data from the first one, two, three, four, or five rounds. In the regressions underlying the table, D_M represents a dummy variable as before: it equals 1 for observations from the majority treatment. We report results for both individual-level and session-level clustering.

Table 7: Probit Regression (Session-level Clustering)

	Posterior									
	Individual-level Clustering					Session-level Clustering				
	Round: 1	Round: 1-2	Round: 1-3	Round: 1-4	Round: 1-5	Round: 1	Round: 1-2	Round: 1-3	Round: 1-4	Round: 1-5
D_M	0.0319*	0.0377***	0.0440***	0.0330***	0.0440***	0.0319	0.0377*	0.0440**	0.0330**	0.0440***
	(0.0177)	(0.0133)	(0.0122)	(0.00984)	(0.00953)	(0.0236)	(0.0208)	(0.0186)	(0.0112)	(0.0103)
Constant	0.627***	0.683***	0.696***	0.715***	0.700***	0.627***	0.683***	0.696***	0.715***	0.700***
	(0.0146)	(0.0113)	(0.0102)	(0.00859)	(0.00813)	(0.0205)	(0.0181)	(0.0162)	(0.00973)	(0.00837)
N	115	229	344	458	573	115	229	344	458	573

Standard errors in parentheses

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

When clustering errors at the individual level, we reach a $p < 0.01$ significance level utilizing only the first two rounds of data. When clustering errors at the session level, we reach a $p < 0.05$ significance level utilizing data from the first three rounds, while a $p < 0.01$ significance level is reached by utilizing data from the first five rounds. Thus, the fundamental patterns in our data are robustly present from the very start of our sessions, when interactions with others in the session are severely limited.

3.4.3 Learning

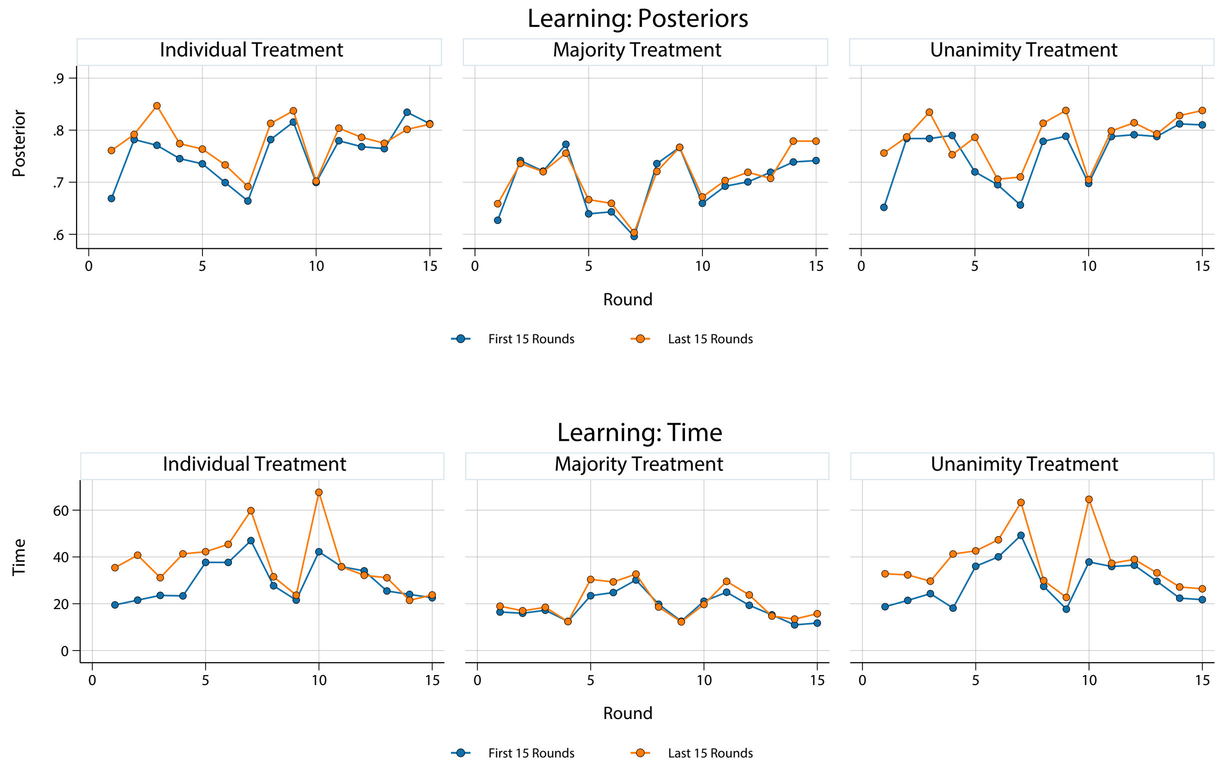
Next, we compare individual-level choices made in each dynamic treatment in the first and last 15 rounds. Recall that in the last 15 rounds, participants experienced the same sample paths (albeit mirrored). Thus, we have a highly controlled environment to study learning. Figure 6 depicts how choices evolve.

As can be seen, in terms of both the posteriors at which participants cast their votes and the time they took, there is a remarkable similarity between the individual and unanimity treatment. Furthermore, the sample path itself heavily influences both the choice of posterior and time. For example, in sample path 10, which is repeated 15 rounds later as sample path 25, we see that participants in the individual and unanimity treatment spend a lot of time. Consequently, due to the decreasing thresholds we identify, they submit their votes with lower posteriors.

3.4.4 Group Influence

Participants do not appear to be influenced by prior group members' choices in our dynamic treatments, as shown in Table 8 here. The table reports results from an individual-level fixed effects regression of the posterior with which a participant cast a vote in round t, on the round number, *Round*, as well as the difference between the posterior with which they cast a vote in

Figure 6: Learning in Dynamic Treatments



round $t-1$, from the mean posterior with which other group members cast a vote in round $t-1$, denoted $Difference_{t-1}$. The $Constant$ captures the average treatment fixed effect. Each column represents a separate fixed-effects regression, for the different dynamic treatments, for either all 30 rounds, the first 15 rounds, or the last 15 rounds (we use individual-level clustering, since the clustering level must match the fixed effects level).

If participants are influenced by their group members, we expect the estimated coefficient on $Difference_{t-1}$ to be negative and statistically significant. For example, when a participant voted with a posterior higher than the rest of the group, group influence would lead the difference to be positive: if the participant is influenced by the group's decisions, she should decrease the posterior with which she casts her vote in the next round. Table 8 here illustrates that there is no such adjustment.

3.5 Demand for Agency – Second and Third Voters Voter

Table 9 presents a regression similar to the one presented in the Appendix of the main text. The dependent variable here is the difference between the posterior of the third and second vote. Since

Table 8: Group Effects in Dynamic Treatments

	Individual			Majority			Unanimity		
	All	First 15	Last 15	All	First 15	Last 15	All	First 15	Last 15
Round	0.00211***	0.00595***	0.00108	0.00136***	0.00240*	0.00414***	0.00201***	0.00380***	0.00364***
	(0.000461)	(0.000951)	(0.000956)	(0.000404)	(0.00132)	(0.000711)	(0.000301)	(0.000708)	(0.000776)
$Difference_{t-1}$				0.0198	0.0170	-0.0227	0.0433	0.0352	-0.0322
				(0.0437)	(0.0759)	(0.0500)	(0.0283)	(0.0334)	(0.0393)
Constant	0.734***	0.707***	0.755***	0.679***	0.678***	0.607***	0.742***	0.731***	0.700***
	(0.00714)	(0.00761)	(0.0220)	(0.00661)	(0.0114)	(0.0164)	(0.00482)	(0.00602)	(0.0179)
N	1020	510	510	728	339	389	1392	672	720

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

in the majority treatment only two votes are required for a decision to be made, this regression utilizes data only from the unanimity treatment and the simulated individual treatment.[4]

Table 9: Stopping Posteriors: Third and Second Voters

	$(p_3 - p_2)$
Constant	0.186***
	(0.0204)
d_U	-0.0794
	(0.0498)
p_2	-0.548***
	(0.0492)
$p_2 \times d_U$	0.100*
	(0.0561)
Last 15	0.0228***
	(0.00765)
Last 15$\times d_U$	-0.00942
	(0.00780)
Slow	-0.00672
	(0.0221)
Slow$\times d_U$	-0.00266
	(0.0126)
N	330518

Standard errors in parentheses
Process-level clustering
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As can be seen, there is no statistically significant difference between the intercepts in the simulated individual treatment and in the unanimity treatment. In contrast, the coefficient of $p_2 \times d_U$ is statistically significant at the 10% significance level. Thus, the unanimity treatment is associated with a slightly flatter slope than the simulated individual treatment. However, since its intercept is also lower, the difference between the two remains rather small.

[4]Since p_1 can take values between 0.5 and 1, before running the regression, we re-normalize all the values of p_1 by subtracting 0.5. Thus, the intercept corresponds to the additional posterior the third voter places when the second voter cast a vote with a posterior of 0.5.

4 Static Treatment: Additional Analysis

4.1 Observed and Simulated Static Treatment Groups

As for our dynamic treatments, in addition to the cumulative distribution plots and the Kolmogorov-Smirnov tests reported in the main text, we present regressions in which we estimate the mean time waited in the observed and simulated group treatments. As in Section 3.1, we denote by d_{Sim} the dummy variable that equals 0 for observed data points, and 1 for simulated data points. In Table 10 above, the constant captures the mean time waited in the observed data, whereas d_{Sim} captures the difference in the mean time waited between the observed and simulated data. We cluster errors on the individual level.

Table 10: Observed and Simulated Static Treatment Groups

	Time in Seconds	
	Majority	Unanimity
d_{Sim}	5.571***	15.63***
	(1.892)	(2.926)
Constant	36.25***	40.46***
	(1.375)	(1.185)
N	300480	300450

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

In line with our discussion in the main text, information-collection durations are significantly shorter in both the static majority and the static unanimity treatments relative to those generated by simulated groups utilizing the same rules, respectively. Furthermore, this reduction in information-collection is significantly more pronounced for our unanimity treatment than for our majority treatment.

4.2 Static Treatment Comparisons

The regressions reported in Table 11 echo some of the observations made in the text and illustrate the impact of experience in our static treatments. Each column represents a separate regression; standard errors are clustered at the individual level. In the majority and unanimity treatment, clustering is based on the pivotal voter. We return to versions with no clustering, process-level clustering, as well as additional controls for risk and altruism, in the following section.

Table 11: Static Treatments - Group-Level Regressions

	Seconds Waited		
	All Rounds		Last 15 Rounds
Constant	41.69***	42.92***	40.45***
	(2.309)	(2.244)	(2.716)
d_M	-5.436**	-4.902*	-5.970*
	(2.665)	(2.488)	(3.295)
d_U	-1.222	0.233	-2.676
	(2.582)	(2.475)	(3.311)
Last 15 I		-2.473	
		(1.861)	
Last 15 M		-3.542**	
		(1.482)	
Last 15 U		-5.382***	
		(2.001)	
N	1860	1860	930

Standard errors in parentheses
Individual-level Clustering
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Although participants choose a lower wait time under the unanimity treatment compared to the individual treatment, the difference is not statistically significant.[5] Under majority rule, on average, participants wait 5.44 seconds less than in the individual treatment, a difference that is statistically significant at the 0.05% level. Recall that the optimal wait time is 29.58 seconds. The regressions also illustrate that, at the individual level, participants wait excessively.

Results reported in the second column of Table 11 reveal that, in all three treatments, experience leads to a reduction in the average chosen wait time: the average wait time in the individual, majority, and unanimity treatments drops from 42.92, 38.02, and 43.15 in the first half of sessions to 40.45, 34.48, and 37.77 in the second half, respectively. Over the course of our experiments, participants therefore move toward the theoretically-optimal choice. Nonetheless, this learning has limits: we see virtually no reduction in wait times over the last 5 rounds of sessions. Furthermore, results in the third column of Table 11 demonstrate that coefficients estimated from the last 15 rounds appear remarkably similar to, albeit less significant than, those estimated using our entire data.

[5] Nonetheless, as we soon show, with no clustering, and with process-level clustering, the coefficient of d_U is negative and statistically significant at least at the 0.05% level.

4.3 Risk Aversion, Altruism, and Alternative Clustering

We now analyze alternative specifications for the results reported in Table 11. Namely, we consider analysis absent clustering, and analysis with process-level clustering. Table 12 presents the results. Almost all coefficients rise in significance level under these two clustering methods relative to the specification of Table 11, in which standard errors are clustered at the individual level.

Table 12: Static Treatments - Alternative Clustering

	Seconds Waited					
	No Clustering			Process Level Clustering		
	All Rounds		Last 15 Rounds	All Rounds		Last 15 Rounds
Constant	41.69***	42.92***	40.45***	41.69***	42.92***	40.45***
	(0.492)	(0.691)	(0.743)	(0.576)	(0.970)	(0.430)
d_M	-5.436***	-4.902***	-5.970***	-5.436***	-4.902***	-5.970***
	(0.843)	(1.184)	(1.273)	(0.470)	(0.730)	(0.462)
d_U	-1.222	0.233	-2.676**	-1.222**	0.233	-2.676***
	(0.861)	(1.210)	(1.300)	(0.432)	(0.601)	(0.865)
Last 15 I		-2.473**			-2.473**	
		(0.977)			(0.962)	
Last 15 M		-3.542***			-3.542***	
		(1.360)			(0.670)	
Last 15 U		-5.382***			-5.382***	
		(1.404)			(1.060)	
N	1860	1860	930	1860	1860	930

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

The results presented in Table 13 control for risk aversion and altruism through two explanatory variables: *Tokens Sent* and *Tokens Not Invested*, as described in Section 3.3. We again run an instrumental-variable regression, using the first elicitation as an instrument for the second.

Table 13: Static Treatments - Alternative Specifications

	Seconds Waited					
	All Rounds			Last 15 Rounds		
	No Clustering	Individual Clustering	Process Clustering	No Clustering	Individual Clustering	Process Clustering
Constant	42.67***	42.67***	42.67***	43.95***	43.95***	43.95***
	(1.465)	(7.633)	(0.903)	(2.098)	(8.338)	(0.846)
d_M	-4.555***	-4.555	-4.555***	-5.717***	-5.717	-5.717***
	(1.286)	(4.483)	(0.790)	(1.498)	(5.090)	(0.457)
d_U	0.687	0.687	0.687	-1.927	-1.927	-1.927*
	(1.368)	(4.910)	(0.499)	(1.641)	(5.495)	(1.017)
Last 15 I	-2.473**	-2.473	-2.473***			
	(0.972)	(1.851)	(0.928)			
Last 15 M	-3.542***	-3.542**	-3.542***			
	(1.353)	(1.480)	(0.646)			
Last 15 U	-5.382***	-5.382***	-5.382***			
	(1.397)	(1.966)	(1.023)			
Tokens Sent	-0.0323	-0.0323	-0.0323	-0.106	-0.106	-0.106***
	(0.0476)	(0.210)	(0.0248)	(0.0733)	(0.239)	(0.0314)
Tokens Not Invested	0.00424	0.00424	0.00424	-0.0256	-0.0256	-0.0256***
	(0.0123)	(0.0659)	(0.00518)	(0.0188)	(0.0706)	(0.00760)
N	1860	1860	1860	930	930	930

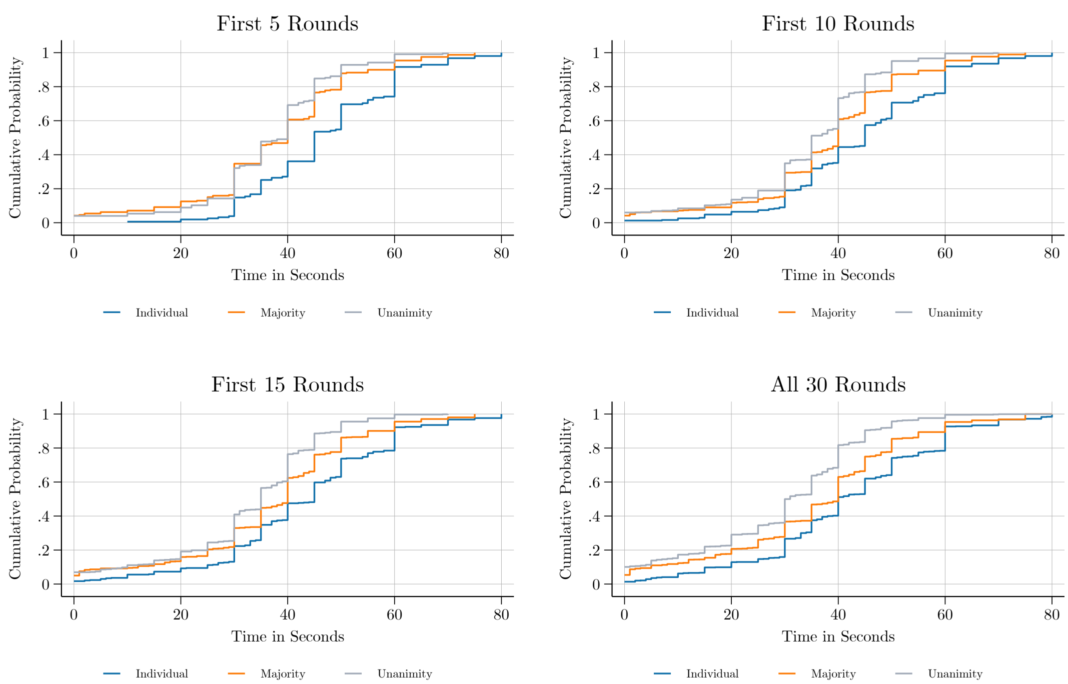
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The first three columns of Table 13 utilize the whole data, whereas the last three columns utilize data from the last 15 rounds only. We present results with no clustering, individual-level clustering, and process-level clustering. As can be seen, the coefficients of *Tokens Sent* and *Tokens Not Invested* appear statistically insignificant in all but the last column, corresponding to the last 15 rounds with errors clustered at the process level. The estimated coefficient of *Tokens Sent* is -0.106, while for *Tokens Not Invested*, the coefficient is estimated at -0.0256. Thus, according to this specification, more altruistic or risk averse participants choose lower waiting times. Nonetheless, these coefficients appear small in magnitude. In particular, altruism and risk aversion seem to have limited explanatory power.

4.4 Session Effects

As for the dynamic treatments, the split into sessions in our data is an unlikely driver of our results. For brevity, we describe a subset of the results presented in Section 3.4.

Figure 7: Effect Present in Initial Rounds in Static Treatments



4.4.1 Presence of Effects in Initial Rounds

The effects we capture are present from our sessions' beginning, before individuals have had a chance to interact extensively with others in the session, as shown in Figure 7 here. The figure show that the comparisons across treatments is present in the first 5, first 10, first 15, as well as in all 30 rounds. Across all our treatments, the distributions of pivotal choices similarly exhibit striking stability over time.

4.4.2 Group Effects

Participants do not appear to be influenced by prior group members' choices in our static treatments either, as shown in Table 14 here. We follow a similar procedure as that underlying Table 8. However, for the static treatments, the variable of choice is time. Thus, we regress the time chosen by a participant in round t, on the round number, *Round*, as well as on the difference between the time she chose in the previous round and the times chosen by her other group members in the previous round, $Difference_{t-1}$. The $Constant$ captures the average treatment fixed effect. Once more, if participants are influenced by their group members, we expect the estimated coefficient on $Difference_{t-1}$ to be negative and statistically significant: if a participant chooses a larger duration than others in the group, we expect her to adjust downwards, and if she chooses a lower duration than others in the group, we expect her to adjust upwards. As Table 14 illustrates, we see no such adjustment.

Table 14: Group Effects in Static Treatments

	Individual			Majority			Unanimity		
	All	First 15	Last 15	All	First 15	Last 15	All	First 15	Last 15
Round	-0.229*	-0.700***	-0.141	-0.268***	-0.671***	-0.0327	-0.444***	-0.776***	-0.234*
	(0.116)	(0.229)	(0.139)	(0.0950)	(0.224)	(0.132)	(0.0895)	(0.187)	(0.126)
$Difference_{t-1}$				0.384**	0.381**	0.0659*	0.140***	0.0668	0.0693
				(0.155)	(0.163)	(0.0362)	(0.0457)	(0.0591)	(0.0565)
Constant	45.23***	48.52***	43.69***	40.74***	44.04***	35.44***	36.15***	38.89***	31.40***
	(1.795)	(1.831)	(3.189)	(1.520)	(1.908)	(3.041)	(1.431)	(1.589)	(2.900)
N	930	465	465	1392	672	720	1305	630	675

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

In fact, the estimated coefficient of $Difference_{t-1}$ is either statistically insignificant or, when significant, positive. This implies that participants are not influenced by the direction of the group. We suspect this captures further individual-level effects not accounted for by the fixed effects: if a participant chose a larger-than-average duration in a previous round, she is likely to do so in future rounds as well.

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