Mental Models, Social Learning & Statistical Discrimination: A Laboratory Study*

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Extended Abstract

1 Motivation

In many economic settings, individuals construct and rely on their subjective understanding of the environment. These *mental models* help organize information, make inferences, and form forecasts. Subjective models that agents adopt could also be *misspecified*, leading them to interpret information in a systematically biased way. A growing literature in economic theory explores the consequences of adopting an incorrect model and its implications for learning and decision-making (Bohren and Hauser, 2021; Esponda and Pouzo, 2016). On the experimental side, a number of recent papers have provided empirical evidence on the ramifications of adopting an incorrect model. Esponda et al. (2023) demonstrate that initial misconceptions induced by information on primitives hinder learning from feedback, while Kendall and Charles (2022) show that modifying the statistical relationship between variables—without changing the underlying causal structure—shapes beliefs in a manner consistent with theoretical predictions.

In addition, empirical studies have examined how subjective models shape beliefs about naturally occurring phenomena: Andre et al. (2023) elicit narratives about macroeconomic variables, Graeber et al. (2022) analyze how individuals select and organize information, and Barron and Fries (2023) study the causal models used by financial advisers. While much of this empirical work focuses on individual learning, there is limited evidence on how mental model heterogeneity manifests in *social learning* environments. Bohren and Hauser (2021) provide a theoretical framework showing that even agents with accurate models may fail to converge to correct long-term beliefs if they are exposed to others with misspecified models. In a related line of research, Bowen et al. (2023) highlight how misconceptions in shared news and low-quality information can contribute to incorrect learning and belief polarization over time.

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2 This Paper

The study empirically investigates a type of social learning in which there are no informational asymmetries. The goal of creating such an environment is to assess how individuals with heterogeneous models adapt their approach when exposed to the choices of others. In principle, these choices are not payoff-relevant, as both agents observe the same amount of information. However, for individuals with low certainty in their own actions, observing others' choices could help them abandon incorrect models and make optimal decisions. In this context, the objective of exposing subjects to external choices is to facilitate learning from others and recognize the suboptimality of their own approach.

Using a theory-informed experiment, we design an abstract inference task and exogenously vary the *type* of exposure to others' choices. Subjects in one treatment group observe the decisions of a participant whose guesses align with the Bayesian benchmark. In another treatment group, subjects are exposed to the choices of a participant who adopts an incorrect model and exhibits behavior consistent with signal neglect. To further disentangle the mechanisms at play, we include a diagnostic treatment condition, where subjects receive not only Bayesian evaluations and simple feedback but also detailed information about the outcomes of their own and others' decisions (not part of this abstract). This condition helps control for confounders related to endogenous sample selection (Esponda and Vespa, 2018).

3 Experimental Design

We designed a between-subjects experiment in which subjects assumed the role of an employer tasked with hiring one of two fictitious workers. Treatments were exogenously assigned in a way that one group observed optimal choices made by another subject, another group observed suboptimal choices, and a third group did not observe any choices made by others.

The in-person experiment was conducted at the University of California San Diego Economics Laboratory. Prior to the main experiment, all subjects were required to correctly answer six comprehension questions to proceed. Across the three main treatments, a total of 164 subjects participated, with the experiment lasting an average of 45 minutes and an average payment of $15.3 per subject.[1]

3.1 Inference Task

The experiment consists of 120 independent rounds in which participants make hiring decisions between two workers—one from a group of Green workers ($k = green$) and one from a group of Orange workers ($k = orange$) . Each group consists of four workers, and each worker has either low, medium, or high ability: $a \in \{l, m, h\}$. In every round, one worker is randomly drawn from each group, and participants must choose one to hire. Participants do not observe the ability levels of two selected workers but can see

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their binary education status: each worker is either educated or not educated. Subjects also know that high-ability workers are always educated ($p_h = \mathbb{P}[educ \mid h] = 1$), medium-ability workers are educated with 90% probability ($p_m = 0.9$) and low-ability workers are never educated ($p_l = 0$). The interface of the experiment is presented in Figure 1.

Participants' earnings depend on the ability and education level of the worker they hire, with higher payoffs for hiring more skilled and educated workers. After each round, they receive the feedback about the ability of the worker they hired along with the earnings that round. At the end of the experiment, subjects' final payment is based on the outcome of one randomly selected round.

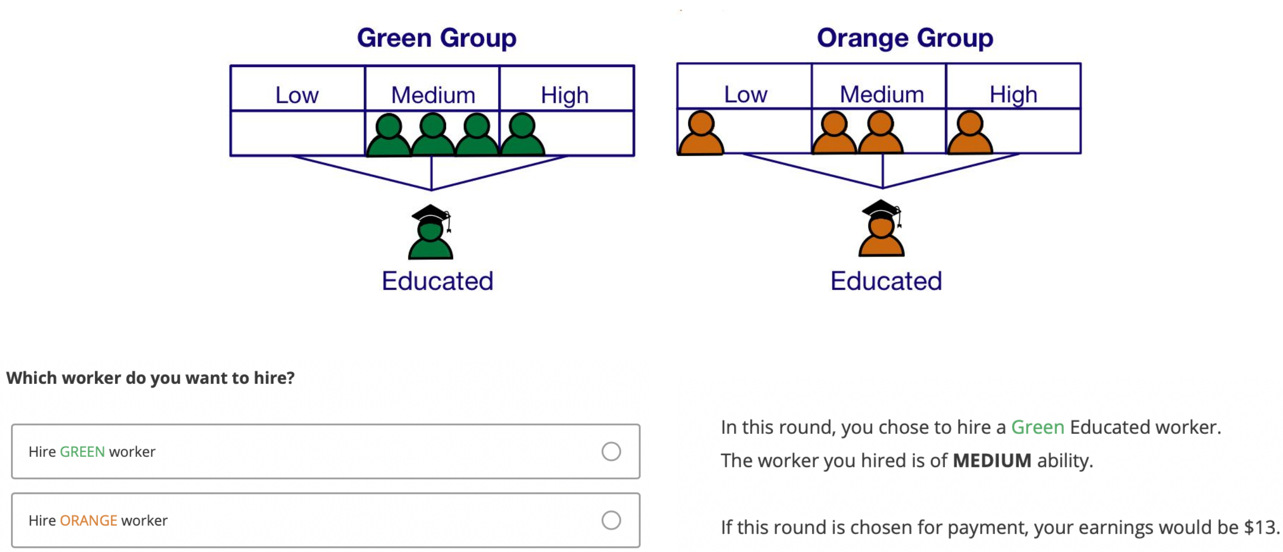

Figure 1: Ability distributions and experiment interface

3.2 Theoretical Benchmark

The ability distributions in two groups as well as the choice of parameters ($p_m = 0.9$) generate many rounds in which both selected workers are educated, as illustrated above. Let k_a represent the proportion of workers of group identity $k \in \{green, orange\}$ who have ability $a \in \{l, m, h\}$. Using Bayes rule, the posterior probability that an educated worker from group g has ability h, is then given by:

$$\mathbb{P}(h \mid educ) = \frac{\mathbb{P}(educ \mid h) \times \mathbb{P}(h)}{\mathbb{P}(educ)} = \frac{p_h \times k_h}{p_h \times k_h + p_m \times k_m + p_l \times k_l} = \frac{k_h}{k_h + 0.9k_m}$$

Noting that $k_h = 0.25, k_m = 0.75$ in the green group while $k_h = 0.25, k_m = 0.5$, it is clear that the posterior belief that the green worker has high ability is *smaller* than that for the orange worker. This implies that the optimal choice consistent with the Bayesian benchmark is to hire the orange worker despite the fact that the green group has on average higher ability.

Crucially, making the optimal binary choice in this environment does not necessarily require subjects to compute conditional probabilities correctly. The key insight is that a worker selected from the orange group cannot have low ability since low-ability workers are never educated ($p_l = 0$). After recognizing this, one only needs to compare the ratio of high-ability to medium-ability workers, which is higher in the orange group. Thus, the focus is on a form of learning that is more general than Bayesian belief updating—the key element is not to neglect the education signal but rather to extract information from it (consistent with Bayesian reasoning). Seeing that both workers are educated, a naive subject under-infers from the signals and hires a worker from the green group, which is associated with higher *average* ability.

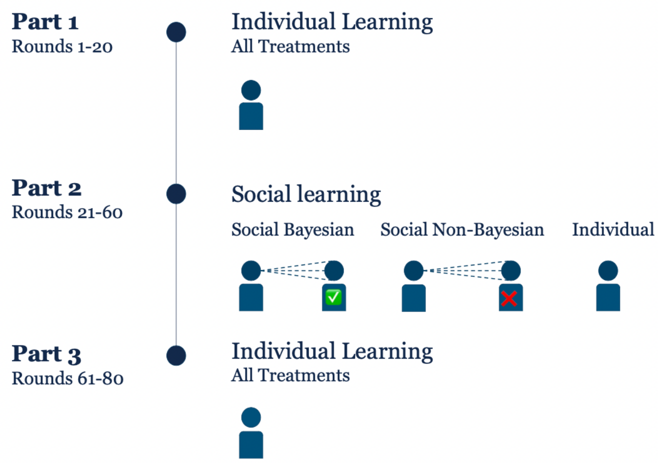

Figure 2: Experiment Structure and Treatment Groups

3.3 Treatments

In a between-subjects experiment, participants are assigned to one of the three treatment groups. In Parts 1 and 3 of the experiment, subjects complete 20 independent rounds of the hiring task described above, regardless of the treatment they are assigned to. After each round, they get feedback about the ability level of the worker they hired and the associated payoff. In Part 2 of the study, we introduce the following

- ***Social Bayesian (SB):*** Subjects in this treatment additionally observe choices made by another participant from one of the previous experimental sessions. They are told that this participant saw the exact same information as them.[2] The participant, whose choices are shown to subjects in this treatment, makes *optimal choices* in all rounds, i. e. consistent with the Bayesian benchmark.

- ***Social Non-Bayesian (SNB)***: Subjects in this treatment observe choices by another participant, identical in structure to *Social Bayesian* treatment. The only difference is that the participant, whose choices are shown to subjects in this treatment, makes *suboptimal choices* in all rounds, i. e. *not* consistent with the Bayesian benchmark and indicative of signal neglect.

[2]Specifically, instructions read: "*For Part 2 of the experiment, in each round you will be provided with the hiring choice of another study participant who took part in the exact same experiment in one of the past sessions – we will call this participant 'participant X'. In each round, participant X saw exactly the same information as you will see.*"

- ***Individual (Ind):*** Subjects in this treatment continue making choices individually, identical to Parts 1 and 3, without any social learning element. This group serves as a reference group.

4 Results

In this section, we describe the main results of the paper. First, the aggregate- and individual-level results showing comparisons between treatments are presented. Second, we dig deeper to understand whether subjects in *Social Bayesian* treatment who make optimal choices when observing external decisions (compliers) truly learn how to behave optimally (learners), or if they simply imitated choices they were observing (imitators). Last, we look at heterogeneity in subjects' choices.

4.1 Main Results

At baseline, fewer than 30% of subjects' choices are optimal, and even with feedback after each round, this only rises to approximately 45% by the end of Part 1. For the next 40 rounds (Part 2), subjects in the social learning treatment groups observe the choices made by another subject without knowing whether they are optimal or not. Exposure to payoff-maximizing choices helps subjects in *Social Bayesian* group to make 12 percentage points (pp) more optimal choices in the last 10 rounds of Part 2 (65% relative to 53% in *Individual* reference group), as Figure 3 illustrates. The size of the treatment effect grows with time to 14 pp ($p = 0.094$) and 22 pp ($p = 0.018$) in the last 3 rounds and in the last 1 round, respectively, as Table 1 shows. Not only do we observe a shift in the mean proportion of optimal choices, but the entire distribution also first-order stochastically dominates that of the control group.

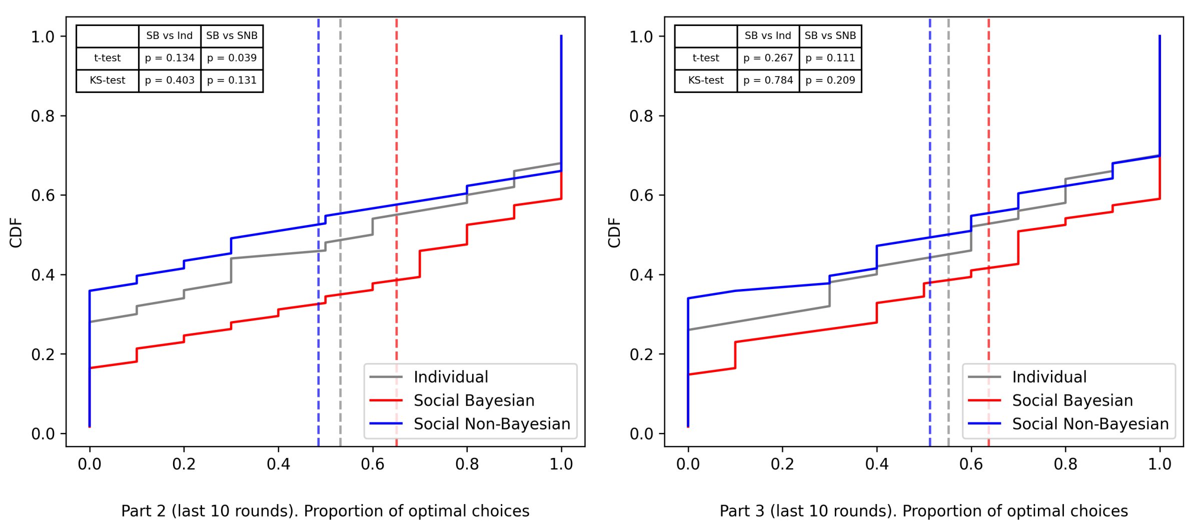

Figure 3: Cumulative Distribution of Optimal Choice Shares

Observing suboptimal choices does affect subjects in *Social Non-Bayesian* treatment marginally as they appear to make 5 pp *less* optimal choices in the last 10 rounds (and last 1 round) of Part 2, although this effect is not statistically significant, as Table 2 reports. In Part 3 of the experiment, subjects in all treatments return to making decisions without observing external choices, exactly as in Part 1. The goal in this part is to assess whether the pattern from the social learning part would persist when subjects are no longer exposed to external decisions.

	Part 2 (social)		Part 3 (individual)	
	Last 3 rounds	Last 1 round	Last 3 rounds	Last 1 round
Social Bayesian	0.138^{*} (0.094)	0.218^{**} (0.018)	0.119 (0.172)	0.156^{*} (0.100)
Social Non-Bayesian	-0.068 (0.445)	-0.048 (0.628)	-0.029 (0.753)	-0.028 (0.776)
Individual	0.540 (0.063)	0.520 (0.071)	0.520^{*} (0.066)	0.500 (0.071)
Number of Observations	492	164	492	164

Table 1: Regression Results on Subject Behavior
Dependent variable: optimal choice $\in \{0, 1\}$; regressors: treatment dummies

As can be seen from the right panels of Figure 3 and Table 1, the general qualitative differences remain in place, although the treatment effect sizes dwindle. The fraction of optimal choices in *Social Bayesian* group is 9 pp higher when we look at the last 10 rounds of Part 3, which grows to 16 pp in the last round ($p = 0.1$). When it comes to *Social Non-Bayesian* subjects, they exhibit 3-4 pp less optimal behavior by the end of Part 3 compared to the individual learning control group.

4.2 Complier Analysis

Having documented a positive effect for *Social Bayesian* subjects who benefit from observing optimal external choices, a natural question arises: to what extent is this treatment effect driven by subjects who have genuinely grasped the optimal approach versus those who merely mimicked the observed choices without understanding the underlying mechanism? In other words, if we focus on compliers in the *Social Bayesian* group, i.e., those who complied with the treatment and made more optimal choices in Part 2, what fraction of them are *learners* and what fraction are *imitators*?

First, we split *Social Bayesian* subjects into two groups: those who made at least 8 optimal choices in the last 10 rounds of Part 2 (compliers, 54%) and those who made less than 8 correct choices (remaining 46%). We then track the evolution of optimal choice proportion in the group of compliers. As Figure 4 portrays, going from Part 2 (social learning) to Part 3 (individual learning) has practically no effect on compliers, depicted in dark red , who continue to make between 90-100% optimal choices even when we stop showing them external decisions.

In the next Part 4 of the experiment, subjects continue making choices on their own but we change the environment – instead of the ability distributions from Figure 1 subjects see an almost a mirror image instead, depicted in Figure 5. While green group still has a higher average ability, we change the probability for medium-ability workers to $p_m = 0.1$ which results in many rounds in which both workers are *not educated* – conditional on observing this, a sophisticated subject would realize that the green selected worker cannot have a high ability ($p_h = 1$), so it is still the optimal choice to hire an orange worker.

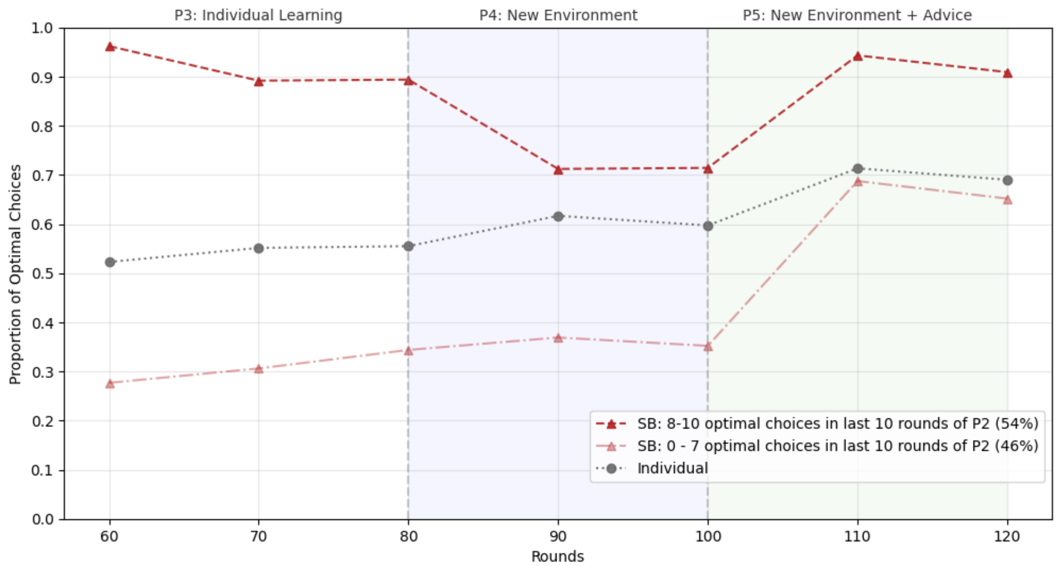

Figure 4: Line Graph

If complier subjects learned the underlying mechanism behind the task they should have no problem making the optimal choice in the new environment, too. However, if their previous optimal choices came from pure imitation we should expect them to find the new setting challenging. The middle panel of Figure 4 shows that the average share of optimal choices among compliers (in dark red) declines substantially from 90% to 70% by the end of Part 4, which is not too far from the share among subjects in *Individual* group who never observed any external choices. This suggests that a considerable portion of average treatment effect in *Social Bayesian* is driven by imitators. In comparison, the proportion of optimal choices among *Social Bayesian* non-compliers (in light red) did not exhibit a fall but instead continued to grow gradually.

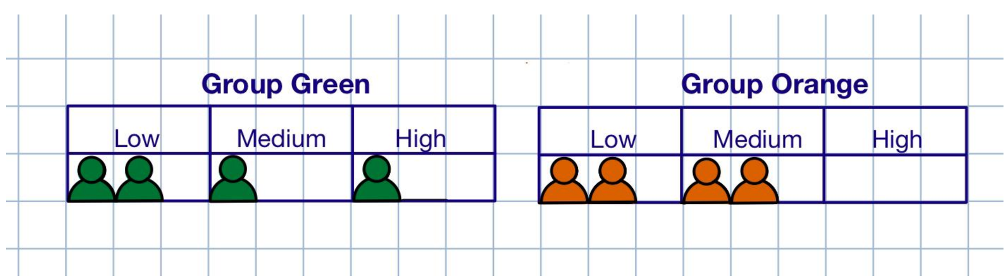

Figure 5: Ability distributions (new environment): Parts 4&5

4.3 Heterogeneity

To further convey the argument made in the previous subsection, we look at the individual heterogeneity in the learning dynamics of *Social Bayesian* subjects instead of looking at the aggregate measures. Each dot in Figure 6 represents one subject in the given treatment group – we are plotting the proportion of optimal choices in the last 10 rounds of Part 2 against the proportion in the last 10 rounds of Part 3. One can immediately see that there are always two clusters at $(0, 0)$ and $(1, 1)$ indicating that quite a lot of subjects make 0% or 100% optimal choices *both* in Part 2 and in Part 3. In the reference *Individual* group, more than two-thirds of subjects are above the 45-degree line consistent with overall learning pattern – experience and feedback help most of control subjects make more optimal choices as time progresses. While most subjects in *Social Bayesian* group are also above 45-degree line, the share is only 57%, which means there are more subjects who *mis-learn* compared to control group.

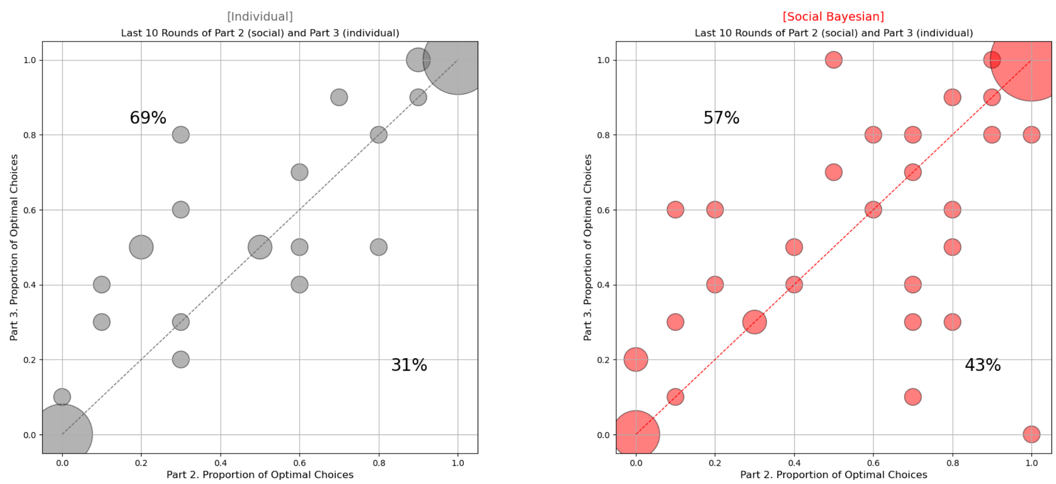

Figure 6: Distribution of Optimal Choice Proportions in Part 2 (social) and Part 3 (individual)

More importantly, once subjects move from the old environment in Part 3 to the new environment in Part 4, the results depicted in Figure 7 are striking. While the learning pattern in *Individual* group remains largely the same with close to two-thirds of subjects staying above the 45-degree level, the pattern in the *Social Bayesian* treatment is reversed. A pervasive 70% of subjects in that group are *below* the 45-degree line – more than two-thirds of subjects make less optimal choices in Part 4 compared to Part 3.

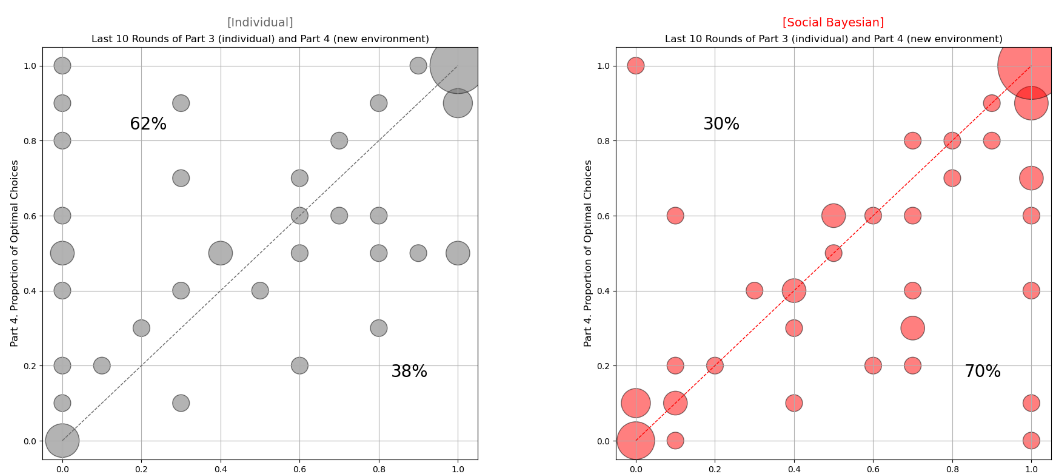

Figure 7: Distribution of Optimal Choice Proportions in Part 3 (individual) and Part 4 (individual-new)

References

Andre, P., Haaland, I., Roth, C., and Wohlfart, J. (2023). Narratives about the macroeconomy. *SSRN Electronic Journal*.

Barron, K. and Fries, T. (2023). Narrative persuasion. *SSRN Electronic Journal*.

Bohren, J. A. and Hauser, D. N. (2021). Learning with heterogeneous misspecified models: Characterization and robustness. *Econometrica*, 89.

Bowen, T. R., Dmitriev, D., and Galperti, S. (2023). Learning from shared news: When abundant information leads to belief polarization. *Quarterly Journal of Economics*, 138.

Esponda, I. and Pouzo, D. (2016). Berk-nash equilibrium: A framework for modeling agents with misspecified models. *Econometrica*, 84.

Esponda, I. and Vespa, E. (2018). Endogenous sample selection: A laboratory study. *Quantitative Economics*, 9(1):183–216.

Esponda, I., Vespa, E., and Yuksel, S. (2023). Mental models and learning: The case of base-rate neglect.

Graeber, T., Zimmermann, F., and Roth, C. (2022). Stories, statistics, and memory. *SSRN Electronic Journal*.

Kendall, C. and Charles, C. (2022). Causal narratives. *SSRN Electronic Journal*.

A Appendix: Additional Figures and Tables

	Part 2: Social Learning		
	Last 10 rounds	Last 3 rounds	Last round
Social Bayesian	0.119	0.138*	0.218**
	(0.079)	(0.082)	(0.091)
Social Non-Bayesian	-0.047	-0.068	-0.048
	(0.086)	(0.089)	(0.099)
Individual (omitted group)	0.532	0.540	0.520
	(0.061)	(0.063)	(0.071)
SB = Ind	$p = 0.134$	$p = 0.094$	$p = 0.018$
SB = SNB	$p = 0.039$	$p = 0.013$	$p = 0.003$
Number of observations	1,640	492	164

Table 2: Proportions of Optimal Choices in Part 2

	Part 3: Individual Learning		
	Last 10 rounds	**Last 3 rounds**	**Last round**
Social Bayesian	0.086	0.119*	0.156*
	(0.077)	(0.087)	(0.094)
Social Non-Bayesian	-0.039	-0.029	-0.028
	(0.083)	(0.093)	(0.099)
Individual (omitted group)	0.552	0.520	0.500
	(0.058)	(0.066)	(0.071)
SB = Ind	$p = 0.266$	$p = 0.172$	$p = 0.100$
SB = SNB	$p = 0.110$	$p = 0.086$	$p = 0.048$
Number of observations	1,640	492	164

Table 3: Proportions of Optimal Choices in Part 3

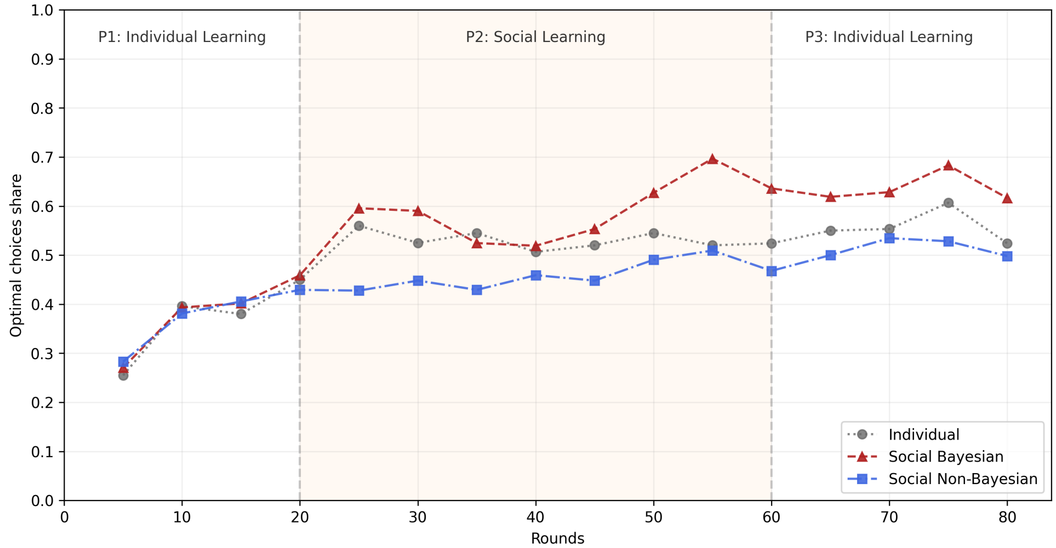

Figure 8: Aggregate Results: Evolution of Optimal Behavior

B Appendix: Theoretical Framework

A **Non-Bayesian** employer adopts a naive (conservative) approach and neglects education signal altogether when observing that both workers are educated. Hence, for them $p^{NB}(a|e,g) = p^{NB}(a|g) = g_a$, and assuming $\pi_{e,h} - \pi_{e,m} = \pi_{e,m} - \pi_{e,l} = \Delta$ their payoff associated with hiring a worker from group g is [3]

$$\pi^N(e,g) = g_l\pi_{e,l} + g_m\pi_{e,m} + g_h\pi_{e,h} = \pi_{e,l} + \Delta(g_m + 2g_h)$$

and the conservative employer, therefore, hires a green worker if

$$\pi^N(e, green) > \pi^N(e, orange) \iff green_m + 2green_h \quad > \quad orange_m + 2orange_h \tag{NB}$$

Note that this condition is equivalent to the green group having a higher average ability than the orange group. This can be seen by using $h - m = m - l$ and showing that[4]

$$green_l \times l + green_m \times m + green_h \times h \quad > \quad orange_l \times l + orange_m \times m + orange_h \times h$$

$$\iff l + (m-l)(green_m + 2green_h) \quad > \quad l + (m-l)(orange_m + 2orange_h)$$

$$\iff green_m + 2green_h \quad > \quad orange_m + 2orange_h$$

The conditions (B) and (NB) derived for hiring a green worker over an orange worker for Bayesian and conservative employers, coupled with the assumption we made that the orange group is disadvantaged

[3] This is because $g_l\pi_{e,l} + g_m\pi_{e,m} + g_h\pi_{e,h} = g_l\pi_{e,l} + g_m(\pi_{e,l} + \Delta) + g_h(\pi_{e,l} + 2\Delta) = \pi_{e,l} + \Delta(g_m + 2g_h)$.

[4] Given all ability levels carrying equal marginal weight, here we use $m = l + (m-l)$ and $h = l + 2(m-l)$.

(lower average ability), give rise to the following observation.

Observation. *If both green and orange workers are educated, then a conservative employer always discriminates against the orange worker. A Bayesian employer, however, discriminates against the orange worker only if (B) is satisfied.*

Naive employers will thus discriminate against orange workers both when it is rational and when it is not rational, leading to excessive discrimination compared to Bayesian employers.

Social Learning

Suppose that two employers i and j perform the identical hiring task described earlier. The set of available actions is given by $A = \{\text{hire green}, \text{hire orange}\}$ with an optimal action $a^* \in A$. Note that ex ante utility for both agents is maximized at a^*, which is in turn governed by the Bayesian benchmark and condition (B) from above. In presence of internal uncertainty about whether her action is optimal, agent i leans toward selecting an action a_i with confidence $c_i = \mathbb{P}_i(a_i = a^*)$ in that action. Let agent i's performance be $q_i = \mathbb{P}(a_i = a^*)$. Thus, c_i is agent's subjective belief that her action is optimal, while q_i is the objective probability of agent selecting the optimal action.

Prior to making her choice, employer i also observes an action selected by employer j and evaluates the probability of that action being optimal, c_j. Agent i then chooses her final action $a_{i|j}$ according to the following:

$$a_{i|j} = \begin{cases} a_j, & \text{with probability } \ \theta_i \\ a_i, & \text{with probability } \ 1 - \theta_i \end{cases}$$

where $\theta_i = \frac{c_j^2}{c_j^2 + c_i^2}$. With probability $1 - \theta_i$ agent i sticks to the original action she was leaning towards, and with the complementary probability she switches to the action that agent j chose. Moreover, this decision is a direct function of agent's relative confidence.