Social Learning, Behavioral Biases and Group Outcomes [*]

Andrea Amelio [†]

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Abstract

In many relevant decision contexts, individuals are affected by a wide array of behavioral biases. Additionally, individuals often have the chance to observe others' decisions and, possibly, change theirs. This paper investigates the impact of social learning on a broad range of behavioral biases, reflecting economically relevant settings. Through an online experiment, I document how social learning can amplify errors stemming from behavioral biases, leading to worse group outcomes. For some tasks, unbiased participants are more likely to imitate biased ones, leading to an amplification of the errors. A misalignment between performance and relative confidence drives this detrimental effect of social learning on group outcomes. These results shed light on settings where cognitive biases affect decision-making in the presence of social learning, such as the interpretation of statistical information or investment decisions. My results suggest that social learning often does not eliminate, and will in fact sometimes exacerbate, the impact of cognitive biases in such settings.

Keywords— *Social Learning, Group Outcomes, Biases, Experiment, Relative Confidence*
JEL Codes: D91, C91, D83

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[†]University of Bonn, Bonn Graduate School of Economics (BGSE): aamelio@uni-bonn.de

1 Introduction

Economics research has documented an extremely rich and diverse set of behavioral biases, both in experimental settings and in the field. The reach of behavioral biases' relevance in economics and finance spans a very wide set of domains such as investment decisions (e.g. Odean, 1999; Barber and Odean, 2000; Frazzini, 2006), labor supply decisions (e.g. Camerer, Babcock, et al., 1997; DellaVigna and Paserman, 2005; Fehr and Goette, 2007), consumer choices (e.g. DellaVigna and Malmendier, 2006; Chetty, Looney, and Kroft, 2009), strategic interactions (e.g. Bosch-Domènech et al., 2002; Johnson et al., 2002), and many more. Crucially, these biases are usually studied with a focus on individual decisions and outcomes. However, we do not act, and make mistakes, in isolation, but constantly observe others and learn from them. For example, we observe our peers to inform crucial decisions in our lives, such as education and investment choices. We also turn to strangers on social media to better understand important political developments, to interpret recently released data about the economy, or the latest statistical facts about public health. This raises the question of whether and how observing and learning from others — social learning — mitigates biases.

For instance, consider the example of a group of retail investors discussing the quality of the new CEO of a company, who has been in charge for one month. The stock price has been decreasing in the last weeks, but, during the same period, the market sector to which the company belongs has been decreasing by larger margins. Some investors might correctly take this into account, while others may *fail to account for the noise* intrinsic in the new information, thus overreacting to it. Each of the investors forms independently their beliefs about the new CEO after learning about the stock price trend and subsequently reveals their assessment to the others. In this setting, how would this form of social learning affect investors' beliefs? Would social learning increase or decrease the number of biased, overreacting, investors?

Generalizing the questions emerging from the example, this paper investigates the extent to which social learning can amplify or curb errors caused by a variety of economically relevant behavioral biases, and how this impacts group outcomes, that is the prevalence of the bias in a group. The answer to this question is prima facie unclear. The reason is that classic social learning settings in economics presume that people know that those they observe have information that they do not have. However, in the context of overcoming cognitive biases, individuals might not realize that others have more accurate information for problem-solving. As a result, they might disregard others' actions as mistakes if they differ from their own, reducing the potential of social learning to mitigate biases. In fact, if unbiased individuals are less confident in their decisions, they may imitate the behavior of biased ones, amplifying the prevalence of mistakes in groups.

To illustrate this point, I propose a simple conceptual framework in which an agent: (i) faces a task and chooses an action, (ii) observes a set of actions from agents who performed an identical task, and (iii) selects one of the observed actions or sticks with the initial action. Agents are prone to mistakes, and this is common knowledge, hence they will hold beliefs concerning the optimality of their and of the observed actions. In principle, agents differ in their probability of committing mistakes, that is they have different levels of performance. The model incorporates the concept of relative confidence as a regulator of social learning behavior. Relative confidence is increasing in the agent's confidence in their action, and decreasing in their assessment of the probability of the other agents' actions being optimal. In other words, relative confidence can be thought of as the difference between confidence in one's own action and confidence in the observed action. A key assumption is that, in any given task, relative confidence is structurally related to relative performance. Crucially, in this framework, when the correlation between relative confidence and relative performance is negative, social learning will increase the group bias and vice versa. The goal of the model is to convey the key intuitions formally and to derive clear predictions for the experimental investigation.

In light of this purpose, I set up a series of preregistered online experiments in which participants undertake a series of cognitive tasks, and can learn from other participants. Each task reflects a well-studied and economically relevant behavioral bias. Specifically, I study the following ten biases: *failure to condition on contingencies* (AC), *correlation neglect* (CN), *following misleading intuition* (CRT), *exponential growth bias* (EGB), *failure in constrained optimization* (KS), *1/N heuristic* (PC), *gambler's fallacy* (GF), *sample size neglect* (SSN), *failure to account for noise* (RM), *thinking about average instead of marginal costs/benefits* (TM).[1,2] In the *Baseline* condition, each task is characterized by five steps, in which participants: (i) provide their answer to the task, (ii) provide their confidence in their answer, (iii) are exposed to another participant's answer to the exact same task, (iv) provide their assessment of the optimality probability of the other participant's answer, and (v) have the opportunity to change their initial answer. Relative confidence is constructed as the difference between the quantities elicited in steps (ii) and (iv).

The experimental setup I illustrate differs in two key aspects from the canonical social learning experiments in the literature, mainly inspired by Anderson and Holt's (1997) influential paper. First, I employ different tasks, each with a correct solution that can be reached with the provided information. In paradigms à la Anderson and Holt (1997) the task is always one in which participants observe a private, noisy, signal about some unobservable state and then sequentially provide their choice for the true state. Second, none of the tasks that I selected feature *external uncertainty*. The latter is intrinsic in environments with imprecise information: as the observed signal is noisy, it is structurally not possible to be certain about what the true state is, even

[1]The fact that these cognitive biases play a relevant role in economic and financial decisions is largely documented in the literature. The early finding that investors typically do not sufficiently diversify, is explained by correlation neglect (Chinco, Hartzmark, and Sussman, 2022; Laudenbach, Ungeheuer, and Weber, 2022). Also, even when investors diversify, a relevant portion of them employ the 1/N heuristics in building their portfolios (Benartzi and Thaler, 2001). Stango and Zinman (2009) show how exponential growth bias accounts for sub-optimal saving behavior, accounting for other relevant factors including financial sophistication. The influence of sample size neglect and gambler's fallacy has been documented in betting (e.g. Camerer, 1989) and financial markets (Baquero, 2006). Frederick (2005) reports an extremely strong relationship of cognitive reflection scores with risk and time preferences. Rees-Jones and Taubinsky (2019) show that individuals fail to apply marginal tax rates and argue its relevance in designing tax schedules. Failure to properly condition on contingencies has been proposed as an explanation for the winner's curse (Charness and Levin, 2009). In a recent literature review on the topic, Niederle and Vespa (2023) connect failure of contingent thinking to college admission problems and health insurance choice.

[2]See Table 1 in Section 3.2 and Table C.4 in Appendix C.4 for a list of references for the ten tasks and a detailed description, respectively.

knowing perfectly how to interpret it. The absence of external uncertainty in the selected tasks has an important implication. In canonical social learning experiments, participants are aware that others possess valuable private information. On the other hand, in this setting, participants might not recognize when others have a better understanding of how to solve a task, and could therefore dismiss contrasting actions as mistakes.

The experiment produces three main findings. First, for each task, there is a positive share of participants switching from their initial action. This provides evidence of how participants are prone to learn from other participant's actions in the absence of external uncertainty. Second, crucially, the impact of social learning on group outcomes differs across tasks. Overall, social learning has a significant negative impact on four tasks (RM, SSN, CN, and TM), a significant positive impact on four tasks (GF, CRT, EGB, and KS), and a non-significant impact on the remaining two tasks (AC and PC). The puzzling result that social learning amplifies errors for several cognitive biases can be explained in light of the conceptual framework. In fact, the correlation between relative confidence and relative performance has good predictive power on group gains from social learning. For tasks with a large, negative (positive) relative performance-relative confidence correlation, social learning has a negative (positive) impact on group performance, the group gains from social learning are generally increasing in the relative confidence-relative performance correlation. In other words, for tasks in which individuals' relative confidence is misaligned with relative performance, social learning leads to an amplification of errors caused by behavioral biases and, therefore, to a worsening of group outcomes.

In summary, this paper provides two key novel contributions. First, it documents that social learning can be detrimental to group outcomes, that is it may increase the prevalence of a bias in a group of individuals. For example, reconsider the retail investors scenario. As shown in Section 5, social learning worsens group outcomes in the case of failure to account for noise. Hence, these results predict that social learning will increase the share of biased investors, that is the share of investors overreacting to the stock price news. Second, this paper proposes a mechanism to explain why group outcomes worsen, supported by experimental evidence: social learning worsens (improves) group outcomes when relative confidence and relative performance are negatively (positively) correlated. The intuition is that, when the correlation is negative, unbiased individuals, that is individuals who chose the optimal action, observing sub-optimal actions will find those more attractive and switch to those with a higher probability than the switching probability of biased individuals observing an optimal action.

This paper contributes to several strands of the economics literature. First, this work adds to the experimental literature on social learning. Most of this literature is based on paradigms à la Anderson and Holt (1997) (see, for example, Kübler and Weizsäcker, 2004; Cipriani and Guarino, 2005; Drehmann, Oechssler, and Roider, 2005; Alevy, Haigh, and List, 2007; Eyster, Rabin, and Weizsäcker, 2018 Angrisani et al., August 2021 Conlon et al., 2022). In this paradigm, all participants observe a private, noisy, signal about some unobservable state and then sequentially provide their choice for the true state. My contribution to this strand of literature is twofold. First, I employ tasks in which there is no external uncertainty. Hence, unlike the existing literature, I do not focus on situations in which participants' incentive to learn from others is based on private information. Instead, participants may want to imitate, or dismiss, others based on their beliefs in others' people ability to better understand and solve the task at hand. Second, I explore the impact of social learning on a wide range of well-studied and economically relevant cognitive biases. While the canonical social learning experiments are all focused on sequential learning in a noisy information environment, focusing on whether individuals rationally learn from others,[3] I can explore how many types of mistakes are influenced by social learning. Oprea and Yuksel (2021) and Grunewald, Klockmann, Schenk, and Siemens (2023) also study how different forms of social learning affect biases, but they specifically focus on motivated beliefs.

Second, this paper is related to the literature on overconfidence, and more specifically to the one on overplacement (following overconfidence classification by Moore and Healy, 2008). This literature has documented how individuals often erroneously believe to be better than others (Svenson, 1981; Camerer and Lovallo, 1997; Williams and Gilovich, 2008; Benoît, Dubra, and Moore, 2015), and how this belief varies with task difficulty, with an inversion of this tendency for harder tasks (Moore and Kim, 2004; Moore and Cain, 2007; Moore and Healy, 2008). While this literature focuses on the average overplacement and how this varies across different settings, in this work, I focus on the correlation between placement (relative confidence) and relative performance and its relation with the impact of social learning. Specifically, I show that when relative confidence is not well-calibrated, social learning amplifies the effect of cognitive biases.

Third, this paper contributes to the literature on *internal* uncertainty or *imprecision.*[4] A central idea in this literature is that uncertainty does not need to be a structural feature of the decision environment, but may stem from the complexity of the decision-making process (Gabaix, 2019; Khaw, Li, and Woodford, 2020; Enke and Graeber, 2023). An additional insight from the current paper is to show how internal uncertainty is relevant to social learning. Moreover, to the best of my knowledge, this paper is the first to elicit participants' beliefs about other participants' performances, showing how the combination of this and internal uncertainty regulates learning behavior.

Finally, and in relation to the point mentioned above, this paper connects to the branch of literature discussing the impact of behavioral biases on aggregate quantities (e.g. Russell and Thaler, 1985; Barberis and Thaler, 2003; Fehr and Tyran, 2005; Charness and Sutter, 2012; Lacetera, Pope, and Sydnor, 2012). In particular, this work relates to Enke, Graeber, and Oprea (2023), who study whether and to what extent institutions filter out behavioral biases and impact aggregate outcomes. The authors show that for some tasks institutions perform well in filtering out biases, while for other tasks aggregation worsens efficiency, arguing that the effectiveness of institutions depends on how well-calibrated are participants in evaluating their performance, on average, in each task. The present paper differs from Enke, Graeber, and Oprea (2023) in two key aspects. First, this paper studies a different — in their language — institution: social learning. Therefore, it contributes to the social learning literature, tackling existing questions on underreaction to others' actions and providing novel evidence on the impact of social learning on behavioral biases. Second, this paper also studies participants' assessment of other participants' performances, and not only their confidence, which plays a

[3] Weizsäcker's (2010) meta-analysis shows how participants tend to underreact to other participants' actions: participants need to observe a large amount of information (actions from others) before contradicting their private signal.

[4] See Woodford (2020) for a review of key concepts from psychophysics and economics applications.

key role in a social learning framework. In other words, this paper studies relative confidence calibration, as opposed to confidence calibration.

The remainder of the paper is structured as follows. Section 2 illustrates a simple formal framework, to convey the key intuitions and derive clear predictions. Section 3 details the experimental design and procedures. Section 4 presents results on social learning and relative confidence, Section 5 on the impact of social learning on group performance and its across-tasks heterogeneity, and Section 6 on the mechanisms behind such heterogeneity. Section 7 concludes and discusses limitations and potential future research avenues.

2 Formal Framework

In this section, I illustrate a simple social learning model in which agents' learning behavior depends on their relative confidence. The purpose of the model is to convey general intuition and to guide the experimental investigation, delivering key predictions. A crucial prediction of this setup is that the way relative confidence is related to relative performance determines the impact of social learning on group performance.

2.1 Setup

Consider a set of N agents performing an identical task. There is a set of available actions A and an optimal action $a^* \in A$. All agents have the same objective function, maximized in a^*. However, In order to figure out the optimal action, agents have to go through a complex cognitive process. I identify the latter as the source of *internal uncertainty.* The latter manifests in that the agent is aware that the action he chooses may in fact be sub-optimal. Hence, agent i will select action a_i, having confidence $c_{i,i} = Pr_i(a_i = a^*)$ in that action. $c_{i,i}$ is i's subjective belief about their own action optimality. For the purpose of this exposition, it is not necessary to define how each agent selects their action or each agent distribution over A. However, let agent's i *performance* be $p_i = Pr(X_i)$, with $X_i = I(a_i = a^*)$. The agent's performance is then the objective probability of agent i selecting the optimal action.

Afterward, agent i observes the vector of actions selected by other agents $A_{-i} = [a_1, .., a_{i-1}, a_{i+1}, .., a_N]$ and assesses the probability of each of those actions being optimal, with the vector of such probabilities being $C_{i,-i} = [c_{i,1}, .., c_{i,i-1}, c_{i,i+1}, .., c_{i,N}]$. Finally, agent i selects their *learning action* l_i, that is the action selected after having observed the actions from other agents.

To assess to what extent social learning is beneficial for group performance, it is necessary to define a measure for that. Let Θ be the *pre-learning optimality rate*:

$$\Theta = \frac{1}{N} \sum_{i=1}^{N} X_i. \tag{1}$$

Hence, its expected value will be:

$$\theta = \mathbf{E}[\Theta] = \frac{1}{N} \sum_{i=1}^{N} p_i. \tag{2}$$

Similarly, it is possible to define the *social learning optimality rate* as

$$\Theta_{SL} = \frac{1}{N}\sum_{i=1}^{N} L_i, \tag{3}$$

with $L_i = I(l_i = a^*)$, and $\theta_{SL} = E[\Theta_{SL}]$. Now, it is possible to define the gain from social learning as

$$\mathcal{G} = \theta_{SL} - \theta. \tag{4}$$

If $\mathcal{G} > 0$ social learning increases group performance and vice versa. To define θ_{SL}, and hence $\mathcal{G}$, it is necessary to characterize l_i.

2.2 Relative Confidence and Social Learning

The learning action l_i is chosen as follows:

$$l_i = \begin{cases} a_{-i}, \text{ with probability } \gamma\mu_i \\ a_i, \text{ with probability } 1-\gamma\mu_i, \end{cases} \tag{5}$$

with $-i$ being such that $c_{i,-i} \in \max_{c_{i,j}} C_{i,-i}$ and $\mu_i = \frac{(c_{i,-i})^2}{(c_{i,-i})^2+c_{i,i}^2}$. Hence, agent i only considers the action from agent *-i*, which is the one that he believes has the highest performance. Under this assumption, μ_i is increasing in relative confidence $c_{i,-i}/c_{i,i}$. With probability $1-\gamma\mu_i$ agent i sticks to his previous action a_i, otherwise, he switches to a_{-i}, where γ represents the sensitivity of switching probability to relative confidence.
Now, assume the relationship between relative confidence and relative performance can be approximated by the following:

$$\frac{c_{i,-i}}{c_{i,i}} = \alpha + \beta\frac{p_{-i}}{p_i}, \tag{6}$$

with $\beta \in \mathbf{R}$ and α such that $c_{i,-i}/c_{i,i} > 0$. If $\beta > 0$, agent's i relative performance increase implies an increase in relative confidence in a_{-i} as opposed to a_i. Throughout the paper, β is referred to as *relative confidence-relative performance correlation.* This correlation should be thought of as being *context-dependent.* For example, in the experimental setup, the relative confidence-relative performance correlation is a structural property of each task: depending on the task features the correlation varies, affecting how social learning impacts group outcomes.

To sum up, this framework illustrates a setting in which social learning behavior is reduced to a binary decision: (i) sticking to the initially chosen action a_i, or (ii) switching to the observed action a_{-i}. This decision directly depends on the agent's relative confidence assessment, which in turn is directly related to relative performance. Hence, as argued below, the relative confidence-relative performance correlation determines social learning impact on group performance.

2.3 Predictions

Prediction 1. *Switching probability $\gamma\mu_i$ is increasing in relative confidence $\frac{c_{i,-i}}{c_{i,i}}$.*

This is more appropriately a model assumption, but it is still relevant to test, especially because the relationship between relative confidence and switching probability lays the foundation for the rest of the conceptual framework.

Prediction 2. *If $\beta > 0$ ($\beta < 0$), then $\mathcal{G} > 0$ ($\mathcal{G} < 0$), that is if relative performance and relative confidence are positively (negatively) correlated, social learning leads to an group performance gain (loss). $\mathcal{G}$ is increasing (decreasing) in β.*

When $\beta > 0$ agents who are better performing are also more confident in their actions, compared to others. Hence, better agents will tend to not switch from their actions, while poor-performing agents will tend to, leading to a gain in group performance due to learning. The opposite would hold for $\beta < 0$.

Prediction 3. *If $\beta > 0$ ($\beta < 0$), at the limit, consensus emerges, with the consensus action being $a = a^*$ ($a \neq a^*$).*

In this specific information structure in which all agents observe everyone else's action, it is possible to show, iterating the argument from Prediction 2, that: (i) social learning improves group outcomes in each iteration, (ii) consensus emerges at the limit, and (iii) the consensus leads to all (none of the) agents choosing the optimal action.[5] In the following section, I illustrate the experimental design and the different experimental conditions built to investigate the different predictions.

3 Experimental Design

The aim is to design an experimental framework to investigate two main questions. First, does social learning reduce or amplify errors induced by biases? Second, does the impact depend on the type of bias? If yes, what are the mechanisms driving this difference?

To answer these questions, I set up an online experiment using ten different cognitive tasks, with the following features: (i) each task reflects a well-studied, economically relevant, cognitive bias; (ii) tasks have simple instructions and relatively short completion time; (iii) in each task there should be room for learning, that is it should not be too easy or too hard to learn from other participant's answers; (iv) tasks should feature no external uncertainty.[6] The order of the tasks is randomized.

3.1 Tasks Selection

The ten selected tasks are a subset of the fifteen tasks used in Enke, Graeber, and Oprea (2023), selected based on the fitness for the social learning framework and the absence of external uncertainty.[7] The absence of external uncertainty is relevant for two identification purposes. First, with the presence of uncertainty in the task, it is not possible to disentangle underreaction (overreaction) from underlearning (overlearning), despite the fact that these have possibly different

[5] One of the experimental conditions, *GroupLearning*, investigates iterated learning and the emergence of consensus in this framework. The key measure of interest is the quality of the consensus action, compared to the average quality of the pre-learning actions. See Section 3.1 for further details.

[6] For additional details on how tasks have been selected see Section 3.2. See Table C.4 in Appendix C.4 for a list and detailed description of the ten tasks.

[7] See their work for a discussion of how the tasks have been selected to fulfill the criterium of economic relevance.

root causes.[8] Second, and related, part of the goal of this work is to study the role of relative confidence in regulating social learning. The absence of uncertainty in the tasks allows for a cleaner identification of this effect. Hence, *Belief Updating* (BU) and *Base Rate Neglect* (BRN) tasks are excluded from the set of 15 tasks used in Enke, Graeber, and Oprea (2023). I also excluded 3 other tasks: *Iterated Reasoning* (IR), *Equilibrium Reasoning* (EQ), and *Wason Task* (WAS). The first two have been excluded because recognizing an optimal (or improving) answer would have been trivial for participants, making the learning process uninteresting to study. Relatedly, from pilot data, it emerged that 100% of participants switched in the learning phase of *Wason Task*, leading to no variability in one of the key outcomes of the experiment. Table 1 lists the ten selected tasks and the associated behavioral bias and Table C.4 in Appendix C.4 provides a more detailed description. Screenshots of task instructions are provided in Appendix C.3.

Task	**Bias/Description**
	Information Processing and Statistical Reasoning
Correlation neglect (CN)	Failing to account for non-independence of data in inference.
	Adaptation of tasks from Enke and Zimmermann (2019).
Gambler's fallacy (GF)	Failing to properly attribute independence to iid draws.
	Coin flipping task adapted from Dohmen, Falk, Huffman, Marklein, and Sunde (2009).
Sample size neglect (SSN)	Failing to account for effect of sample size on precision of data.
	Adaptation of hospital problem from Kahneman and Tversky (1972); Bar-Hillel (1979).
Regression to mean (RM)	Failing to account for noise / failure to recognize regression to the mean.
	Adaptation of task from Kahneman and Tversky (1973).
Acquiring-a-company (AC)	Failing to properly condition on contingencies, à la the Winner's Curse.
	Bidding task against computer as in Charness and Levin (2009).
	Logic
Cognitive reflection test (CRT)	Following intuitive but misleading 'System 1' intuitions.
	Adaptation of Frederick (2005).
	Constrained Optimization
Knapsack (KS)	Failure to identify optimal bundle in constrained optimization problem.
	Knapsack problems taken from Murawski and Bossaerts (2016).
	Financial Reasoning
Thinking at the Margin (TM)	Thinking about average instead of marginal costs/benefits.
	Adaptation of marginal tax task from Rees-Jones and Taubinsky (2019).
Portfolio choice (PC)	Failure to construct efficient portfolios due to 1/N heuristic.
	Choose optimal portfolio vs. dominated 1/N portfolio.
Exponential growth bias (EGB)	Underestimate the exponential effects of compounding.
	Interest rate forecasting problem adapted from Levy and Tasoff (2016).

Table 1: Selected tasks descriptions and references, as reported in Enke, Graeber, and Oprea (2023).

3.2 Structure and Experimental Conditions

For each task, participants: (i) provide their answer for the current task; (ii) report their confidence about their answer; (iii) are shown an answer from another participant; (iv) provide an assessment of the probability of the observed answer being optimal; (v) participants are given a chance to change the answer provided in (i). This structure concerns the *Baseline* condition.

[8] See Section 1 for a discussion on this point.

Table 2 summarizes each treatment condition's key features and differences. In what follows, I provide additional details on the elicitation procedures in the *Baseline* condition. Afterward, I illustrate more in-depth the structure and the purpose of the additional treatments.

Treatment	Observe Others' Confidence	Observe Multiple Answers	Multiple Learning Rounds	Multiple Tasks
Baseline	✗	✗	✗	✓
OtherConf	✓	✗	✗	✓
GroupLearning	✓	✓	✓	✗

Table 2: Experimental Conditions Main Features

Confidence Elicitation

Once participants provide their solution to the task, they are asked to provide their confidence level. This elicitation takes place for all participants, in each task. The question is posed in terms of certainty about decision optimality, following Enke and Graeber (2023) and Enke, Graeber, and Oprea (2023). Figure 1 shows a screenshot of confidence elicitation.

As argued by Enke, Graeber, and Oprea (2023), confidence elicitation may impact the following decisions, which may speak against a within-subjects design, such as the one employed in this paper. On the other hand, a within-subject design allows for establishing a more direct link between confidence elicitations and social learning behavior, which of primary relevance to study the mechanism illustrated in Section 6.

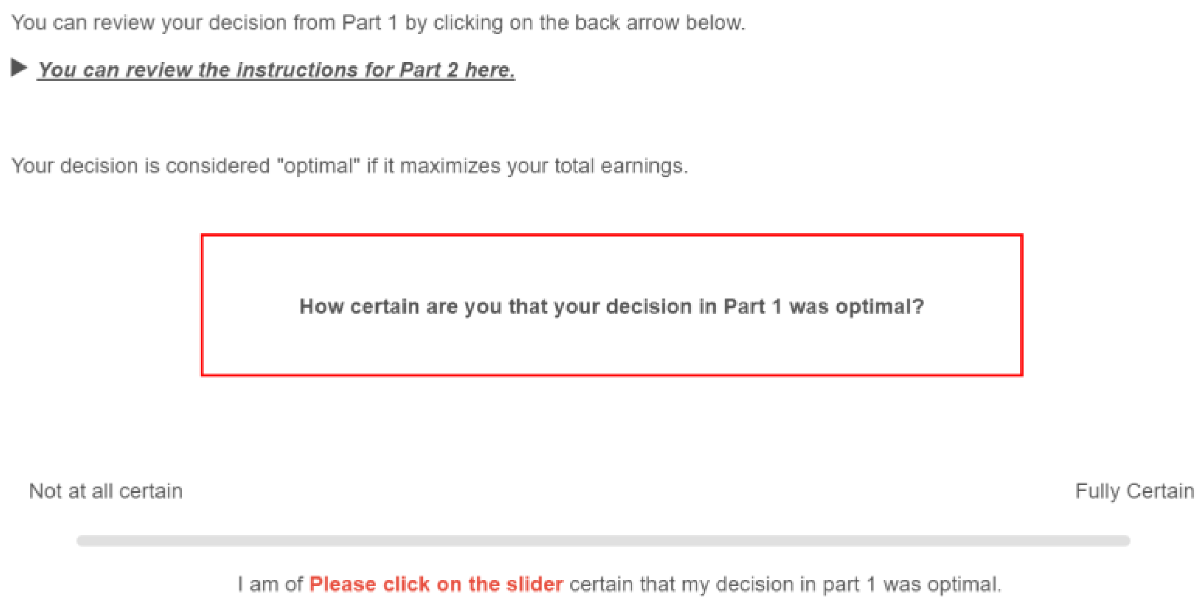


Figure 1: Example of $c_{i,i}$ elicitation.

Learning Phase

In the learning phase, participants observe an answer provided by another participant to the exact same task (a_{-i}). After that, they provide their assessment of the probability that the observed answer is optimal ($c_{i,-i}$) and, finally, participants may change their initial answer to a new *learning answer* (l_i). Importantly, a_{-i} is *always different* from a_i. This design choice is aimed at maximizing power: if $a_i = a_{-i}$ there would be no room for learning and that observation would be excluded from the sample.[9] This could raise three kinds of concerns. First, selecting which answer to show to participants based on their previous actions could generate an endogeneity problem. In short, I tackle this by applying a correction to the measure of net aggregate gains from social learning. Details on this are provided in Section 5. Second, one may be worried that participants are being deceived, as they are not being shown a random answer. However, as reported in Figure C.4 in Appendix C.1, the instructions of the task state that they will be shown another participant's answer, without specifying that the answer is randomly drawn. Figure 2 and Figure 3 show a screenshot of $c_{i,-i}$ elicitation and of l_i elicitation respectively. Third, participants' answers may change if they believe that the answers that are being shown are non-random or computer generated. To tackle this issue, in the final block of the experiment, participants are asked to report if they had any comments on the shown answers from other participants. This way, it is possible to exclude participants who report concerns about the shown answers' legitimacy.

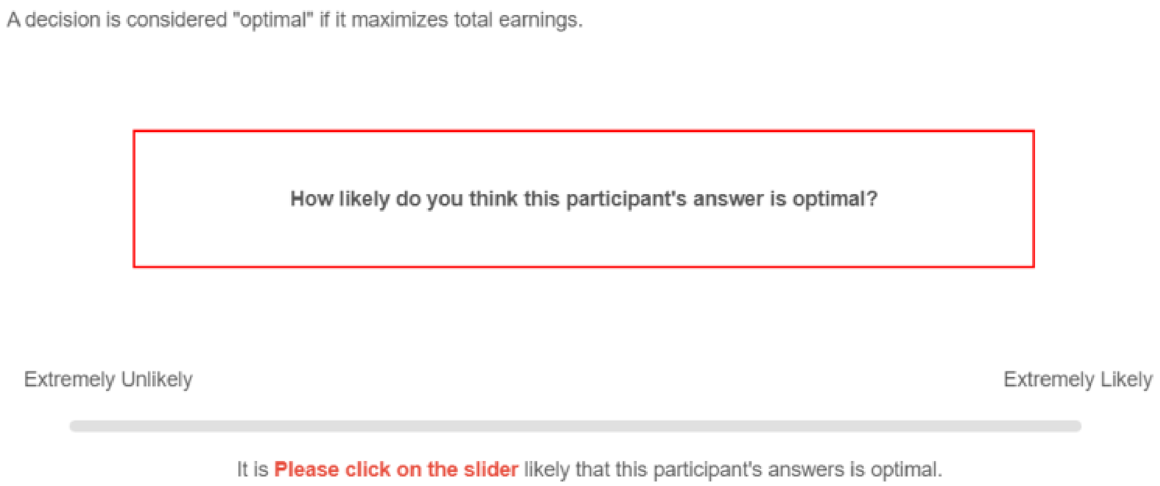


Figure 2: Example of elicitation of observed answer optimality ($c_{i,-i}$).

[9]Clearly, this statement relies on the assumption that a participant would stick with their initial choice, after observing an identical action.

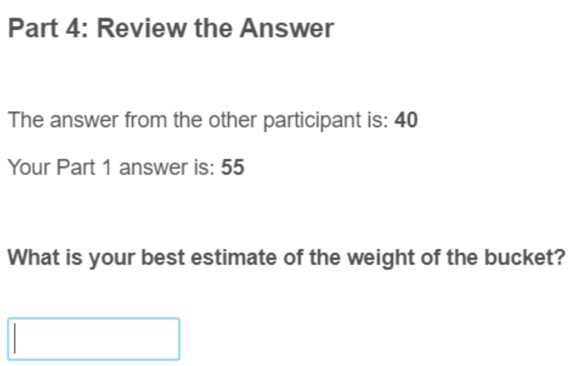


Figure 3: Example of learning action (l_i) elicitation from Correlation Neglect (CN) task.

OtherConf **Condition**

In the *OtherConf* treatment, participants observe directly other participants' confidence, as opposed to guessing the probability of the observed answer being optimal. Specifically, given the observed answer (a_{-i}), participants are shown the median confidence level associated with that specific answer.[10]

In principle, there may be social learning settings in which individuals infer (e.g. social learning settings in which only actions or performances from others are available, à la Moore and Healy, 2008) or observe (e.g. in a conversation or a debate) others' confidence levels. Relatedly, it has been shown that inferred or observed levels of confidence influence the extent to which individuals react to information provided by others (e.g. Van Zant and Berger, 2019; Amelio, 2022), and also that individuals seem to be sophisticated and strategically manipulate their confidence level to be more persuasive (Schwardmann and Van der Weele, 2019). Hence, this treatment is a natural extension to the *Baseline* treatment. The aim is to assess whether and to what extent the results in the *Baseline* treatment extend to a setting in which participants observe others' confidence, which is a natural and relevant social learning framework per se.

GroupLearning **Condition**

Three additional questions that naturally arise starting from the *Baseline* condition are: (i) If social learning takes place in groups of multiple participants, as opposed to pairs, how does this impact findings? (ii) Does having multiple learning rounds, as opposed to one, improve or hinder the impact of learning on group outcomes? (iii) Do people converge on a specific, possibly incorrect, answer? This condition tackles all of these questions.

In the *GroupLearning* condition, participants first independently complete a task.[11] As in other treatments, they provide an answer and subsequently their confidence level. Afterward, each participant is matched with three other participants, forming a group of four. The groups

[10] An alternative design choice could have been to show the confidence level of a random participant who provided a specific answer. However, this approach would have generated noisier data.

[11] Unlike the other two experimental conditions, participants only solve one task. Out of the ten tasks in the *Baseline*, two have been selected: CRT and RM (see the following section for more details on each task).

are formed to contain two participants who answered optimally and two who did not.[12] All participants observe the answers and confidence levels of all group members. Finally, each participant may change their answer and their confidence level in their (potentially different) answer. This procedure is repeated for a total of three rounds, in which the four participants stay unchanged. A focus on the first learning round allows to investigate the impact of social learning in a group, as opposed to social learning from an individual, on group outcomes. Analyzing the answers' dynamics over rounds, with a special focus on the last one, allows to investigate whether repeated social learning leads to a different impact on group outcomes compared to single-round learning. Additionally, it is possible to look for evidence of convergence on a specific answer and assess if this convergence is beneficial or detrimental to the group.

3.3 Logistics

The experiment was conducted on Qualtrics, using Prolific as a recruiting platform. In total, 1700 participants were recruited, of which 300 for *Baseline*, 200 for *OtherConf*, and 1200 for *GroupLearning*. For the *Baseline* treatment, participants took on average approximately 22 minutes to complete the study and received on average £3. Hence, the hourly wage was approximately £8. The median completion time for *OtherConf* was approximately 20 minutes with a comparable compensation to *Baseline*. Finally, for *GroupLearning* the median time was approximately 5 minutes, including the time to be matched with other participants, with an average compensation of approximately £0.8.

Following instructions, participants had to complete a set of comprehension questions, to ensure that they successfully understood the essential parts of the experiment. Participants who failed to answer at least one of the questions were screened out. Appendix C.2 reports screenshots of all the comprehension questions. Both sample sizes and exclusion restrictions have been preregistered.

4 Learning Behavior and Relative Confidence

The first piece of evidence I present concerns general patterns in social learning behavior and how this behavior is modulated by relative confidence. Figure 4 reports the probability of switching by task, that is the share of participants such that $a_i \neq l_i$.

[12] In order to not distort participants' perception about the distribution of answers and to minimize attrition rates, two tasks with an optimality rate as close as possible to 50% have been selected.

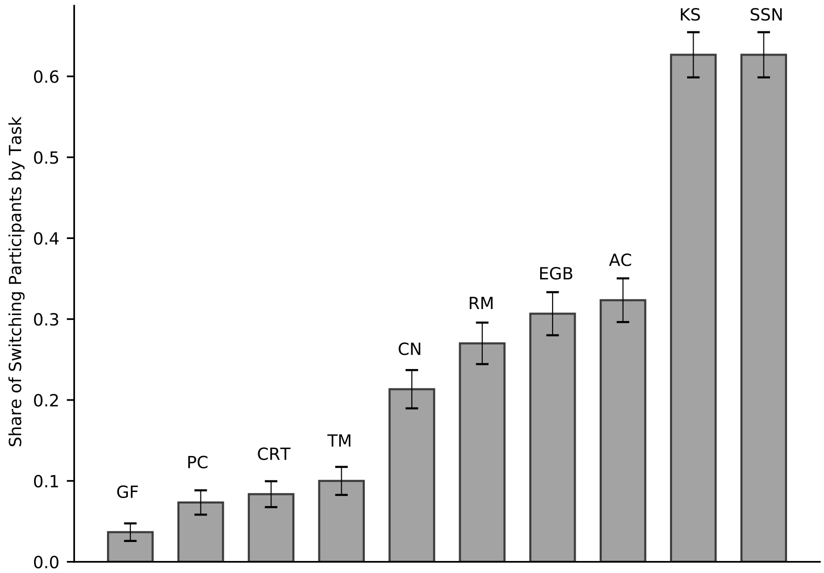


Figure 4: Switching rates by task. A participant is classified as a switcher if their learning action (l_i) is different from their initial action (a_i). Task codes: AC=Acquiring-a-company; CN=Correlation neglect; CRT=Cognitive reflection test; EGB=Exponential growth calculation; GF= Predict sequence of draws; KS=Knapsack; PC=Portfolio choice; RM=Regression to the mean/Attribution; SSN=Account for sample size; TM=Marginal thinking.

Two aspects are worth stressing. First, there seems to be consistent heterogeneity in switching rates across tasks. Second, the switching rates are always significantly larger than 0. Hence, even in the absence of external uncertainty, there seems to be an incentive to learn from other participants' actions.[13]

Given that participants seem to be willing to switch to other actions, that is, in other words, that a form of social learning is taking place in the data, what does regulate their learning behavior? Figure 5 reports the share of participants with $c_{i,i} < c_{i,-i}$ for switchers and non-switchers, respectively. This can be interpreted as the probability of being relatively less confident in a_i compared to a_{-i}, conditional on having, as opposed to not having, switched. The figure shows quite strikingly how switchers in each task always exhibit a significantly higher rate of participants with $c_{i,i} < c_{i,-i}$, although this share varies substantially across tasks.

[13]Clearly, the propensity to switch from the initial answer will also depend on task difficulty. However, as shown by Enke, Graeber, and Oprea (2023), performance and confidence are not necessarily positively correlated, and in some tasks, confidence assessments may be systematically miscalibrated. This calibration, combined with the accuracy with which participants can assess the observed answer quality, determines the mediating effect of relative confidence on the impact of social learning on group outcomes, as argued more in-depth in Section 6.

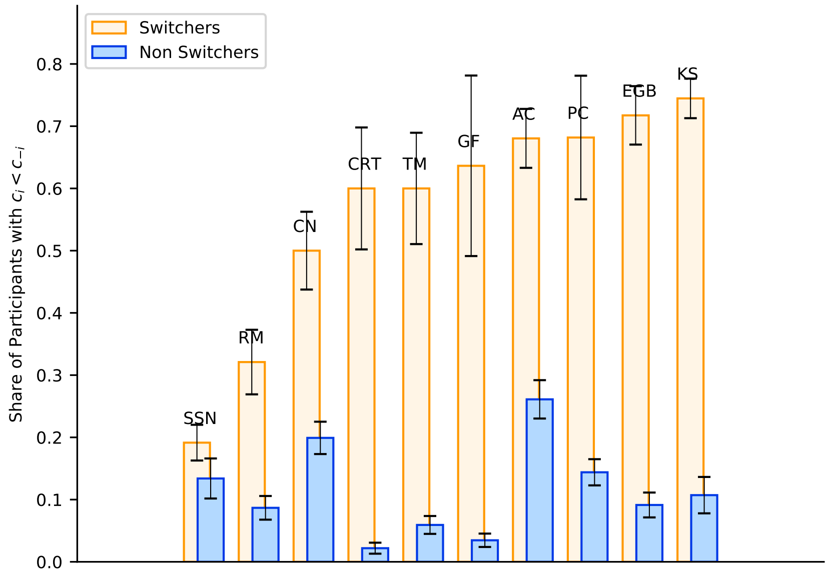


Figure 5: Share of participants with reported confidence lower than the assessed probability of a_{-i} being optimal, by task. Task codes: AC=Acquiring-a-company; CN=Correlation neglect; CRT=Cognitive reflection test; EGB=Exponential growth calculation; GF= Predict sequence of draws; KS=Knapsack; PC=Portfolio choice; RM=Regression to the mean/Attribution; SSN=Account for sample size; TM=Marginal thinking.

Figure 6 reports additional evidence on the relationship between relative confidence and switching behavior, showing the PDF of *relative confidence* for switchers and non-switchers. Relative confidence is computed simply as the difference between confidence and assessed probability of a_{-i} being optimal.[14] Figure 6 also strongly supports the idea that relative confidence represents an important driver in social learning behavior: the two distributions are significantly different,[15] with the non-switchers distribution being more right-skewed.

[14]The reason why relative confidence is not defined exactly as in Section 2, that is the ratio between $c_{i,i}$ and $c_{i,-i}$, is to avoid throwing away observations in case $c_{i,i} = c_{i,-i} = 0$. All results are robust to the alternative definition of relative confidence.

[15]A t-test comparing the mean relative confidence for switchers and non-switchers rejects the null with a $p < 0.001$. Additionally, a two-sample K-S test rejects the null that the two empirical distributions of relative confidence are drawn from the same probability distribution with a $p < 0.001$.

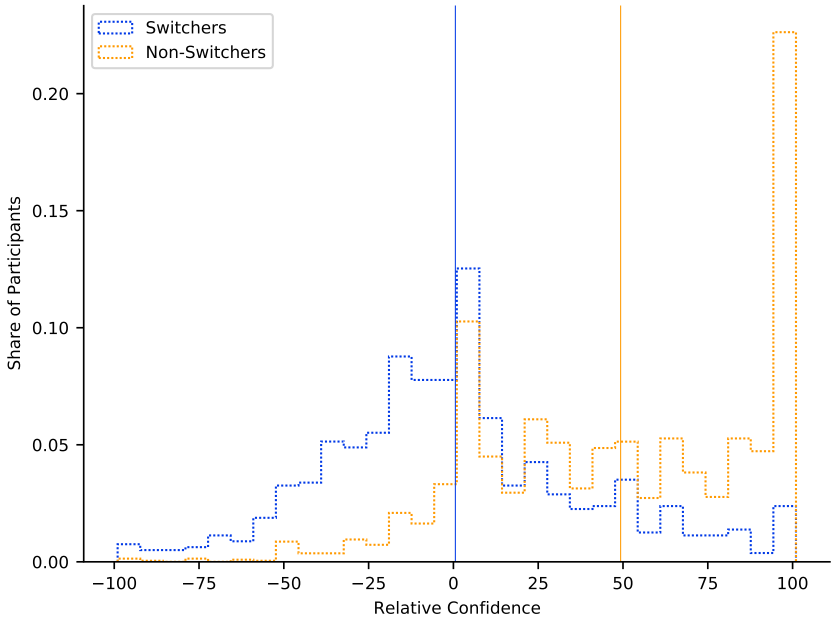


Figure 6: PDF of relative confidence, comparing switchers and non-switchers. Relative confidence in constructed as $c_{i,i} - c_{i,-i}$. The vertical lines represent the distribution means.

5 Impact of Social Learning

Given that participants are willing to switch from their initial action, does learning affect positively or negatively group performance? To answer this question I compare the optimality rates in each task before and after the learning phase. The optimality rate pre-learning (post-learning) is the share of participants choosing the optimal action before (after) learning.

Participants may fall into one of the following four categories, depending on their pre-learning response and their learning behavior: (i) overlearner, (ii) optimal switcher, (iii) underlearner, and (iv) optimal non-switcher. Table 3 summarises the features of each category. Note that, in measuring the impact of social learning, only overlearners and optimal switchers matter, with the former being associated with losses and the latter with gains. Underlearners also represent a sub-optimal behavior, however, by construction, they do not impact changes in optimality rates at the group level. At the same time, the share of undelearners is interesting, as it represents an upper bound for gains from social learning.[16] Figures A.5 and A.4 in the Appendix report the share of overlearners and optimal switchers, respectively, by task.

[16]Moreover, undelearners represent a consistent share of participants across tasks, approximately 39%, that is more than half of the participants who do not switch at all.

	Swicther	Non-Swicther
Optimal a_i	*Overlearner*	*Optimal non-swicther*
Non-optimal a_i	*Optimal swicther*	*Underlearner*

Table 3: The four possible categories of a participant in the learning phase. Optimal/non-optimal a_i *refers to the optimality of the action chosen in the pre-learning phase. Switcher/non-switcher refers to the participant sticking or not to their pre-learning action.*

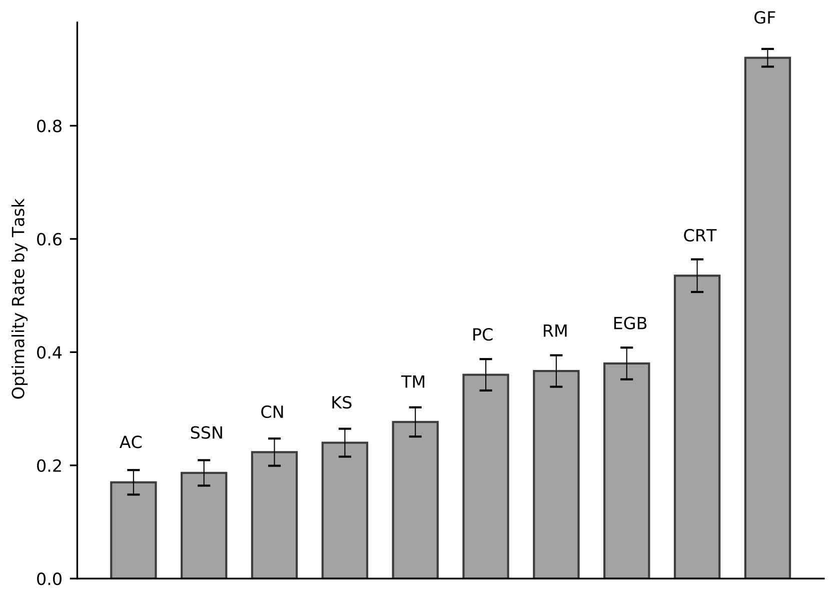


Figure 7: Share of participants choosing the optimal action, before learning, by task. Task codes: AC=Acquiring-a-company; CN=Correlation neglect; CRT=Cognitive reflection test; EGB=Exponential growth calculation; GF= Predict sequence of draws; KS=Knapsack; PC=Portfolio choice; RM=Regression to the mean/Attribution; SSN=Account for sample size; TM=Marginal thinking.

Figure 7 reports the pre-learning optimality rates by task, showing the heterogeneity in performance across tasks. This heterogeneity is particularly relevant given the design choice discussed in Section 3: in the learning phase, participants are always shown a different answer from the one they initially chose. More specifically, participants who took the optimal action were shown a non-optimal answer, and, vice versa, participants who took a sub-optimal action were shown the optimal answer.[17] Hence, the extent to which there is room for gains or losses from learning depends on the pre-learning optimality rate. For example, in a task with a quite low optimality rate, most participants were shown the optimal answer, implying, ceteris paribus, a higher probability of a gain from learning. For this reason, simply taking the difference in optimality rates

[17] The rationale behind this design choice is illustrated in Section 3.

by tasks would not be a clean measure of group gains from learning. To tackle this issue, I build a weighted measure of group gains from learning, taking into account the actual optimality rate in each task:

$$w\_group\_gains_k = p_k \cdot group\_gains_k - (1 - p_k) \cdot group\_losses_k,$$

where p_k is the pre-learning optimality rate in task k; $group\_gains_k$ is the share of participants who switched to an optimal answer from an incorrect one, in task k; vice versa, $group\_losses_k$ is the share of participants who switched from an optimal answer to an incorrect one, in task k. Referring to Table 3, this measure is comparing the *proportions* of *overlearners* and *optimal switchers*. In other words, the weighted group gains are a weighted sum of gains and losses from learning. The weights represent, respectively, the probability of being exposed to an optimal action (p_k) and hence having the chance to gain from learning, and the probability of being exposed to a sub-optimal action ($1 - p_k$) and incurring the possibility of a loss from learning. Alternatively, the weighted gains (losses) can be interpreted as the probability of switching to a correct (wrong) action, having answered wrongly (correctly) in the first step. Therefore, this measure can be interpreted as the *expected group gains* from social learning.[18] Figure 8 reports the weighted group gains from learning for each of the ten cognitive tasks.

[18]This interpretation holds under the assumption that individuals observing an action identical to their initial choice would not switch to another action.

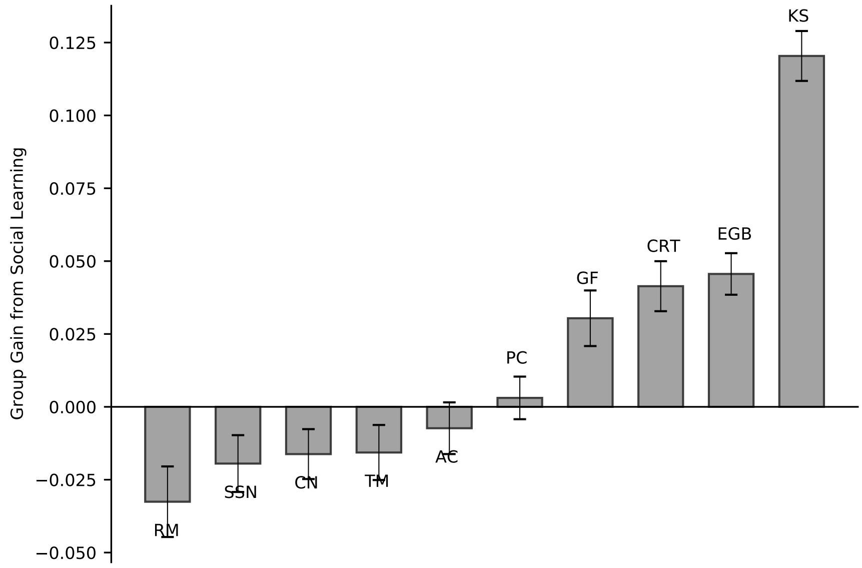


Figure 8: Group gains from social learning, by task. The weighted net gain measure, for each task, is built by weighting gains and losses with the optimality rate in and its complement on 1, respectively. Error bars represent standard errors. Task codes: AC=Acquiring-a-company; CN=Correlation neglect; CRT=Cognitive reflection test; EGB=Exponential growth calculation; GF= Predict sequence of draws; KS=Knapsack; PC=Portfolio choice; RM=Regression to the mean/Attribution; SSN=Account for sample size; TM=Marginal thinking.

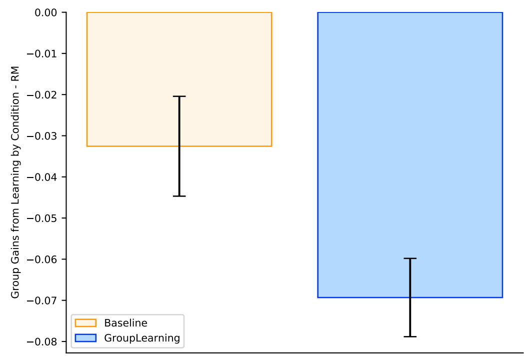
Figure 8 shows clearly that the effect of social learning can be both beneficial and detrimental for group outcomes. Over the ten tasks, four exhibit a significant loss, four a significant gain, and two no significant impact. The net gains range from a loss of approximately 3% (for the RM task) to a gain of approximately 12% (for the KS task). It is interesting to note that these net variations are almost always the result of both gains and losses from social learning, which are usually of a larger, and quite relevant, magnitude.[19] Figures A.4 and A.5 report unweighted gains and losses respectively. The results are very similar for the *OtherConf* condition (see Figure A.23 in Appendix A.7). Interestingly, group gains from learning differ depending on participants' gender, with females gaining less from learning on average (see figure A.20 in Appendix A.6).

In what follows I show how results of *Baseline* and *OtherConf* conditions are robust when social learning takes place in groups and iteratively. Afterward, since the impact of social learning differs across tasks, the following section explores the mechanisms behind this heterogeneity. More specifically, it shows how the relative confidence-relative performance correlation is predictive of group gains from social learning.

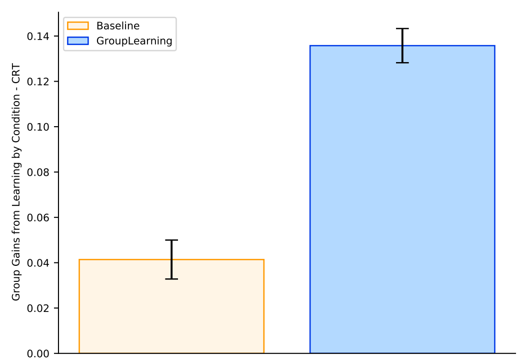
[19]For example, the RM task features 7% of participants switching to the optimal answer and 10% of participants switching from the optimal answer to an incorrect answer.

Group Learning and Multiple Learning Rounds

All the results shown so far concern learning from a single action. In other words, participants were observing another individual participant's answer and deciding whether to stick to their initial action or switch to a different one. However, are results robust to social learning taking place with multiple individuals at the same time? In the *GroupLearning* condition, I focus on this question, using two of the ten tasks studied in the other conditions, RM and CRT. The first (second) has been selected to study group learning in the case of a task characterized by a negative (positive) effect of social learning on group outcomes.[20] For simplicity, here I focus on the RM task, but the results are the same for the CRT task, although in the opposite direction. Figures 9a and 9b compare, for the RM and the CRT task respectively, the group gains from learning for the *Baseline* condition and the *GroupLearning* condition. For the latter, it is important to specify that the gains are calculated for the first round of learning.[21] This allows us to explore the question of whether the results, in terms of the negative impact of social learning on group outcomes, are robust to learning taking place in groups. In fact, the figure shows that not only the result is robust, but that for the *GroupLearning* condition, the losses from learning are approximately doubled for the RM task and tripled for the CRT task.



(a) Group gains (losses) from social learning, for the RM task, comparing the Baseline and the GroupLearning conditions. For the latter, the gains are calculated for the first round of learning. Error bars represent standard errors.



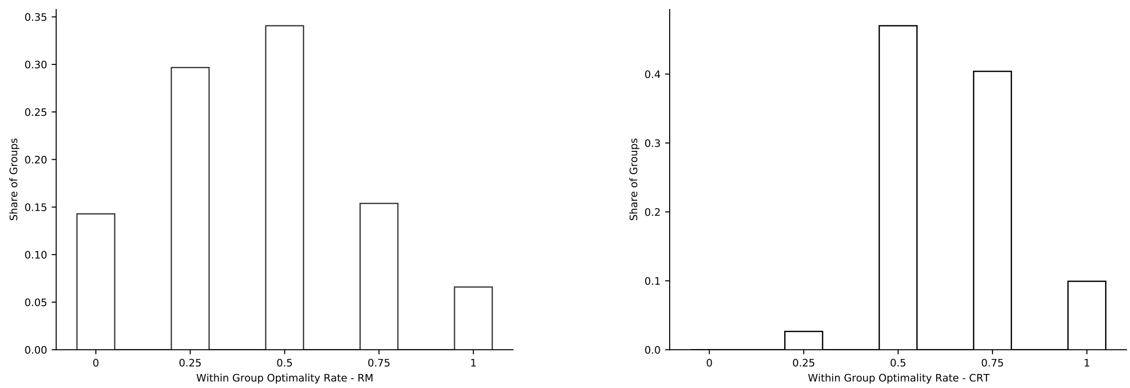
(b) Group gains (losses) from social learning, for the CRT task, comparing the Baseline and the GroupLearning conditions. For the latter, the gains are calculated for the first round of learning. Error bars represent standard errors.

This condition introduces another addition to the *Baseline*, that is participants in a group engage in two additional rounds of learning after the first. Figures 10a and 10b report the second key

[20]For additional details on the structure of the condition and on the selection criteria see Section 3.2. Broadly, the two tasks were selected using the optimality rate before learning. The aim was for the two tasks to have an optimality rate as close as possible to 50%, since this is how groups are built in this treatment. This criterion is preregistered.

[21]The gains are calculated using the weighted measure illustrated in Section 5, although the share of participants with the optimal answer is, by construction, 50%. Hence, the only effect the weighting has in this case is of halving the actual difference between optimal and sub-optimal switchers. Using the latter directly would make the two measures not comparable.

result of this section, concerning the impact of iteration, that is of multiple learning rounds. The figure shows the distribution of within-group optimality rates in the last learning round for both RM and CRT. The results for RM show that approximately 15% of the groups end up with all group members choosing the sub-optimal action and that 30% of the four-participants groups conclude the learning rounds with only one member having stuck with the optimal action. In line with the results shown in Figures 9b and 8, the results for the CRT task are even stronger. Figure 10b shows how no group has zero optimal answers at the end of the learning rounds and that slightly more than 2% of the groups have only one member sticking to the optimal answer. Hence, for CRT, social learning iterations seem to be extremely effective, as almost no group is worse off than before learning.[22]



(a) Distribution of share of optimal answers within each group of four participants in the last learning round, for the RM task.

(b) Distribution of share of optimal answers within each group of four participants in the last learning round, for the CRT task.

Two additional observations are worth mentioning. First, for RM (CRT), the distribution is strongly skewed to the left (right). This means that most of the participants do not benefit (do benefit) from social learning, even when it takes place in groups and even when it is iterated over multiple learning rounds. Second, in line with Prediction 3, Figure 10a (10b) provides evidence for convergence towards the sub-optimal (optimal) action. By design, all groups start with a 50% optimality rate. Out of the groups that end up with a different optimality rate (approximately 65%), approximately two-thirds exhibit a lower one, that is more group members pick the sub-optimal action. A similar, but stronger, consideration can be made for CRT in which, as mentioned, almost all groups end up with a better optimality rate than the starting one. These observations support the view that the negative (positive) impact of social learning on group outcomes in the *Baseline* condition is robust to a setting in which: (i) multiple participants can observe each others' actions, and (ii) participants may learn from each other multiple times. This reinforces the result that the negative or positive impact of social learning documented so far is strongly related to the task or bias at hand. In the next section, I investigate this very aspect and show how a task-specific feature, the relative confidence-relative performance correlation, can account for how social learning impact differs across different tasks.

[22] Recall that, by construction, the initial distribution is that all groups have 50% optimality rate.

6 Relative Confidence-Relative Performance Correlation and Social Learning Impact

The previous section shows how the effect of social learning on group outcomes can vary for different behavioral biases. This section explores the mechanism proposed in the formal framework, based on relative confidence-relative performance correlation. Relative confidence here is defined as the difference between the participant's reported confidence in their answer ($c_{i,i}$) and their assessment of the probability of a_{-i} being optimal ($c_{i,-i}$). In other words, the relative confidence measure is $r_i = c_{i,i} - c_{i,-i}$.[23] Relative performance is a dummy variable, taking the value of 1 if the participant's action (a_i) is optimal and the action she is observing (a_{-i}) is not, and being equal to 0 if the opposite holds. Note that, given how a_{-i} is chosen in the experiment, there is a perfect correspondence between this relative performance dummy and a dummy for optimality. This is because participants whose a_i is optimal are always shown a sub-optimal a_{-i} and vice versa.

Figure A.1 shows how β varies across different tasks. This correlation can be interpreted as the average precision of participants' relative confidence assessments for a given task. For example, if $\beta < 0$, then, on average, participants who are observing the optimal answer (as their pre-learning answer was sub-optimal) will be more confident in their answer and, similarly, participants whose original answer is optimal, and are hence observing a sub-optimal answer, will be relatively less confident in their own answer.

The hypothesis is that this correlation translates into how social learning impacts group performance, through the way relative confidence modulates learning behavior. Figure 11 illustrates the relationship between β and the group gain from social learning. The benefits of social learning on group outcomes increase in β: the line that best fits the points is strongly upward-sloped.[24]This relationship does not seem to be predicted by task difficulty (see Figure 13b) nor by the type of elicited answer (comparing continuous and discrete tasks, see Figure 13a). Additionally, the results do not vary when considering only a sub-sample of participants who did not express any concern or doubt regarding the authenticity of the observed actions, as shown in Figure A.25.[25] Finally, this same result holds for the *OtherConf* condition, that is in the case of participants observing others' reported confidence levels, as shown in Figure 12.

[23]Encoding relative confidence this way allows to also account for the intensive margin of relative confidence in building our measures of interest. Results are robust to a dichotomic encoding of relative confidence, with the variable taking the value of 1 if $c_{i,i} > c_{i,-i}$ and 0 otherwise. Figure A.8 reports results equivalent to Figure 11 with this different encoding for relative confidence.

[24]The confidence-performance correlation, or *confidence calibration*, used in Enke, Graeber, and Oprea (2023), is not predictive of gains from learning as the relative confidence-relative performance correlation, as reported in Figure A.24. This shows how confidence calibration is not sufficient to account for the impact of learning.

[25]As participants are always shown answers that are different from their initial choice, they may doubt the fact that the observed answers are genuine or human-generated. For this reason, at the end of the experiment participants are asked to answer an open-ended question, concerning doubts or comments they may have on observed answers. The figures in the Appendix report the two main results excluding participants who expressed doubts about the authenticity of the observed answers.

Comparing the results in Figure 11 (*Baseline* condition) and Figure 12 (*OtherConf* condition) two main differences emerge. First, CN (correlation neglect) and TM (thinking at the margin) fall in different quadrants of the plane in each condition. Most interestingly, in *OtherConf*, CN exhibits a negative relative confidence-relative performance correlation and, in line with the framework, a group loss from learning, while in *Baseline* CN exhibits a group gain from learning. A potential explanation for this difference is that, for *Baseline*, CN is the task in which switching behavior is the most inconsistent with relative confidence. The latter is, on average, close to zero, indicating a high level of uncertainty from participants. However, in *OtherConf*, participants observe the confidence level associated with the observed action and seem to take it at face value. This may reduce the inconsistency between relative confidence and switching behavior, generating this difference between the two conditions. Second, comparing the intersection of the best fitting line for the two conditions, the one in *OtherConf* is very close to zero, while the one in *Baseline* is strongly negative. The latter implies that, in the *Baseline* condition, for tasks with a zero relative confidence-relative performance correlation, there would be losses from learning. However, in relation to the previous point, this difference is mainly driven by the CN task, so it should be interpreted with caution.

It is important to note that the tasks with the smallest (largest) β are also the ones with the largest losses (gains) from social learning, while the relationship is less striking and noisier for tasks with a β closer to 0. Hence, the data are strongly supportive of the relationship between β and group gains from social learning. However, these results also point toward the need for a larger sample of tasks, as this would allow to (i) generalize this relationship with more confidence, and (ii) observe a more diverse, potentially more extreme, set of relative confidence-relative performance correlations for different tasks, and further test the extensive margin of its impact on gains from social learning.

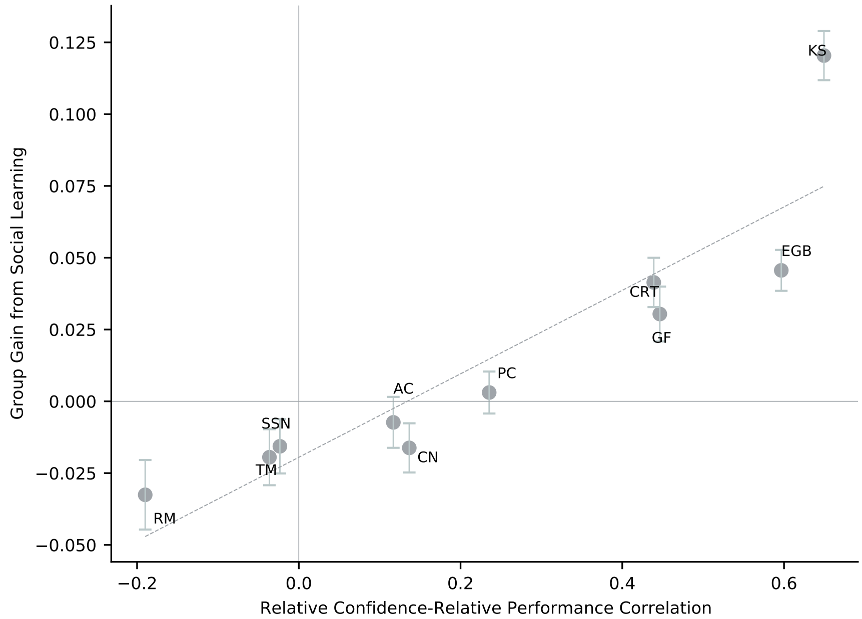


Figure 11: Scatter plot of relative confidence-relative performance correlation (on the x-axis) and the weighted group gain from social learning (on the y-axis). The error bars represent standard errors. Task codes: AC=Acquiring-a-company; CN=Correlation neglect; CRT=Cognitive reflection test; EGB=Exponential growth calculation; GF= Predict sequence of draws; KS=Knapsack; PC=Portfolio choice; RM=Regression to the mean/Attribution; SSN=Account for sample size; TM=Marginal thinking.

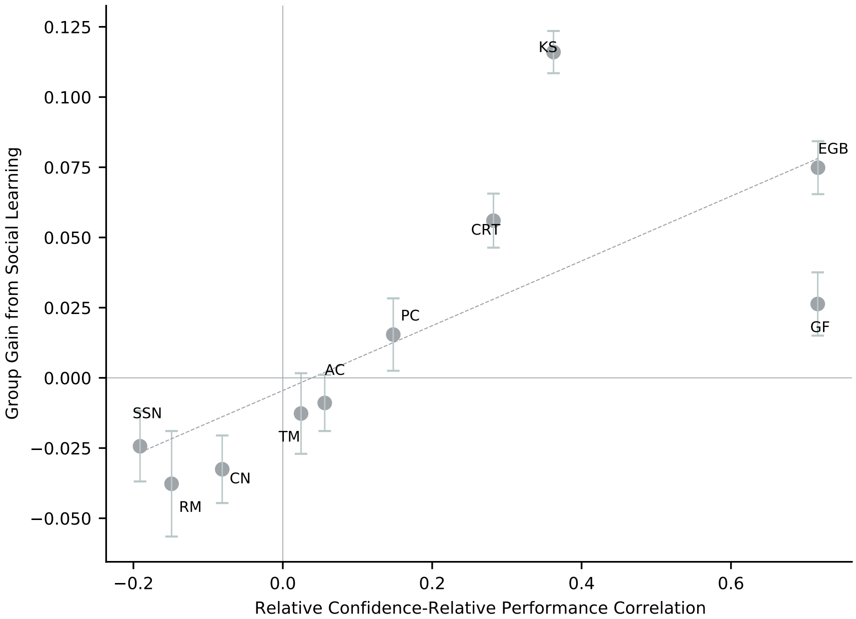


Figure 12: Scatter plot of relative confidence-relative performance correlation (on the x-axis) and the weighted group gain from social learning (on the y-axis), for the OtherConf condition. The error bars represent standard errors. Task codes: AC=Acquiring-a-company; CN=Correlation neglect; CRT=Cognitive reflection test; EGB=Exponential growth calculation; GF= Predict sequence of draws; KS=Knapsack; PC=Portfolio choice; RM=Regression to the mean/Attribution; SSN=Account for sample size; TM=Marginal thinking.

6.1 Relative Confidence Assessment and Task Features

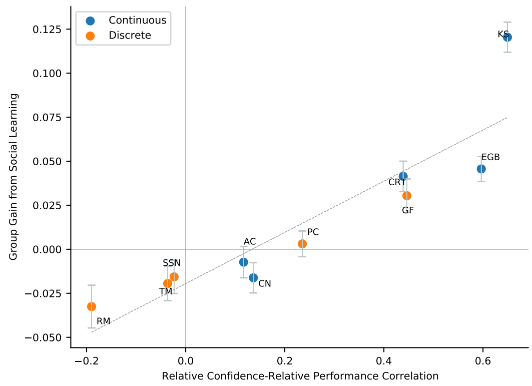
A question that naturally arises from these results is: Which features of the tasks determine the differences in relative confidence-relative performance correlation? In other words, what makes, for example, RM (regression to the mean) a task in which participants struggle to recognize better answers and EGB (exponential growth calculation) a task in which participants seem to benefit from social learning? In what follows, I discuss different explanations and classifications, without however providing a definitive answer to the question.

Misleading Intuitions and Verifiability

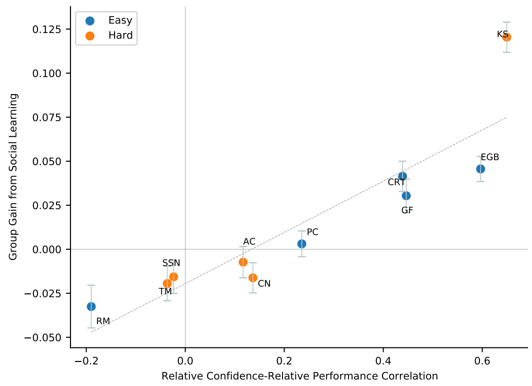
As pointed out by Enke, Graeber, and Oprea (2023), concerning the confidence-performance correlation, misleading intuition could play a relevant role. For example, tasks such as CRT (cognitive reflection test) or CN (correlation neglect), are characterized by a very "attractive" incorrect answer, which participants may be extremely confident in. In an exploratory analysis, Enke, Graeber, and Oprea (2023) use the “peakedness” of the distribution of answers within each task to operationalize the idea of misleading intuitions. Tasks in which a low number of wrong answers are chosen more often would exhibit a high “peakedness” and be associated with misleading intuitions. However, this classification does not seem to fit the evidence on the correlation between relative confidence and relative performance. On the one hand, Figures A.11, A.12, A.16 and A.17 show how CRT, EGB, RM and SSN (sample size neglect) respectively are characterized by a high “peakedness”. On the other hand, the first two tasks exhibit a large positive relative confidence-relative performance correlation, while the opposite holds for the other two. In a social learning framework, a very attractive wrong answer is not sufficient for poorly calibrated relative confidence, as the observed action plays a crucial role as well. For example, CRT is a task with a very attractive incorrect answer, according to the “peakedness” criterion. However, it also exhibits a large share of optimal switchers. In other words, many participants fall for the misleading intuitive answer, but, when presented with the correct answer, they are also very likely to recognize it. Hence, for “peakedness” to play a role in this framework, it is also necessary for the correct answer to be less attractive when compared to the incorrect, intuitive one. In other words, a very attractive wrong answer is not a sufficient condition for social learning to have a negative impact, as a very easily recognizable correct answer (once it is shown) also plays a major role. The idea of “peakedness” is partially related to the concept of *insight* and *non-insight* tasks from the psychology literature. The difference between the two is not strictly defined in the literature, but it can be summarized in the fact that the solution process to insight problems is characterized by a sudden, and possibly incorrect, intuition and a high level of confidence (Metcalfe and Wiebe, 1987; Kounios et al., 2006; Webb, Little, and Cropper, 2016). This is opposed to an analytical and step-by-step procedure for non-insight problems. Once again, this type of classification helps to illuminate the decision-making procedure before learning, but it does not seem to provide further insights about the tendency to recognize correct or incorrect answers from other participants. Finally, a feature that can reasonably play a relevant role in the effectiveness of the learning phase is *ex-post verifiability*, that is the possibility to directly compare two solutions in their optimality levels. The KS and CRT tasks are the only ones that may be classified as ex-post-verifiable and both significant gains from learning. However, as this evidence concerns only two tasks, concluding that ex-post verifiability is a sufficient condition for social learning to be beneficial for group outcomes would be speculative.

Tasks Classifications

The type of available answers in each task may also explain the differences in group gains from learning. Tasks with a definite set of answers, discrete tasks, may differ from tasks with continuous answers in terms of relative confidence and performance. Figure 13a reports the same results as Figure 11, additionally splitting the tasks into discrete and continuous ones. The figure, however, suggests that the split does not explain the relative confidence-relative performance correlation sign. In a similar fashion, Figure 13b splits the ten tasks into two groups, ”Hard” and ”Easy”, based on the optimality rate in the pre-learning phase. Following the psychology literature on the hard-easy effect (Suantak, Bolger, and Ferrell, 1996; Moore and Cain, 2007; Moore and Healy, 2008), people tend to overestimate their performance in hard tasks and underestimate them in easy tasks. Task difficulty, however, does not seem to be predictive of the relative confidence-relative performance correlation, especially when focusing on tasks with a significant one. As with the ”peakedness” case, this explanation seems to fall short because it is focused on the pre-learning action, thus disregarding the features of the learning phase.



(a) Scatter plot of relative confidence-relative performance correlation (on the x-axis) and the weighted net gain from social learning (on the y-axis). The error bars represent standard errors. Tasks are split into two groups, based on the type of required answer. "Discrete" tasks are the ones characterized by closed-ended questions, while continuous are the others. Task codes: AC=Acquiring-a-company; CN=Correlation neglect; CRT=Cognitive reflection test; EGB=Exponential growth calculation; GF= Predict sequence of draws; KS=Knapsack; PC=Portfolio choice; RM=Regression to the mean/Attribution; SSN=Account for sample size; TM=Marginal thinking.



(b) Scatter plot of relative confidence-relative performance correlation (on the x-axis) and the weighted net gain from social learning (on the y-axis). The error bars represent standard errors. Tasks are split into two groups of equal size, with the "Hard" tasks being the five tasks with the lowest pre-learning optimality rate and the "Easy" tasks being the five with the highest optimality rate. Task codes: AC=Acquiring-a-company; CN=Correlation neglect; CRT=Cognitive reflection test; EGB=Exponential growth calculation; GF= Predict sequence of draws; KS=Knapsack; PC=Portfolio choice; RM=Regression to the mean/Attribution; SSN=Account for sample size; TM=Marginal thinking.

7 Conclusion

Behavioral economics has documented an extremely rich set of behavioral biases, which have been shown to be impactful in laboratory and field settings. However, individuals do not make mistakes being in isolation from others, but, instead, observe and learn from other individuals. It is unclear how observing others' actions and beliefs, i.e. social learning, impacts the incidence of behavioral biases. Does social learning reduce or amplify said biases? Through a series of online experiments, I study social learning in a broad set of economically relevant tasks that reflect established behavioral biases. Crucially, this paper studies how social learning impacts group outcomes, that is the incidence of biased individuals among all participants. The evidence shows substantial heterogeneity in the effect social learning has on group outcomes, with the latter worsening for some biases and improving for others as a consequence of learning. This shows how social learning can both reduce and amplify errors induced by behavioral biases. This work also sheds light on the mechanism underlying the heterogeneous effect of social learning, showing how it is strongly predicted by the within-task relative confidence-relative performance correlation. The latter can be interpreted as a combination of the capacity of participants to assess the quality of their own actions (metacognition) and the quality of the answers from other participants, in a specific task.

Applications, Limitations and Further Avenues

The central finding that social learning can amplify biased-induced errors has several real-world applications. As proposed in Section 1, this can be relevant in the political domain. Consider the example formulated in the Introduction, and assume the politician's claim on youth unemployment triggers Sample Size Neglect among some voters. The implication of the experimental results is that unbiased voters would be more likely to change their minds and imitate biased ones, leading to overall less accurate beliefs. This also points toward how communication strategies by politicians may leverage well-known behavioral biases to persuade voters. This paper sheds light on which kinds of biases would persist in an environment in which social learning between voters takes place. The same findings can also be relevant in the domain of non-institutional investment decisions. Following the results, investors failing to account for noise may be more likely to be imitated, spreading overreaction to new information.

More generally, these findings are relevant in any setting in which: (i) decision-makers are affected by one of the studied biases and, (ii) social learning takes place similarly to the experiment. Both conditions point toward the limitations of this work. First, it is not clear whether all the abstract experimental tasks map into applications. Second, a clear criterium to classify biases ex-ante does not emerge in this work. This limits the applicability of results only to the set of ten behavioral biases studied in the paper. Third, it is easy to think of settings in which learning is richer than just observing other people's actions and beliefs. Therefore, a promising research avenue would be to study the impact of social learning on different biases, enriching the existing corpus of evidence. Additionally, documenting how these mechanisms in more applied settings would also represent a relevant contribution. Finally, an extension of this work featuring richer communication structures also represents a potential avenue for future research.

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Appendix A Additional Figures

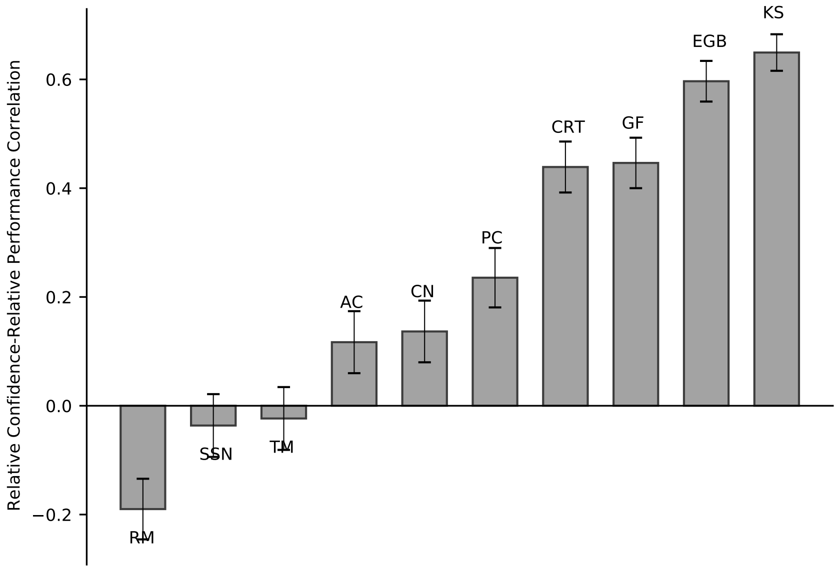


Figure A.1: Relative confidence-relative performance correlation (β), by task. Task codes: AC=Acquiring-a-company; CN=Correlation neglect; CRT=Cognitive reflection test; EGB=Exponential growth calculation; GF= Predict sequence of draws; KS=Knapsack; PC=Portfolio choice; RM=Regression to the mean/Attribution; SSN=Account for sample size; TM=Marginal thinking.

A.1 Relationship between $c_{i,i}$ and $c_{i,-i}$

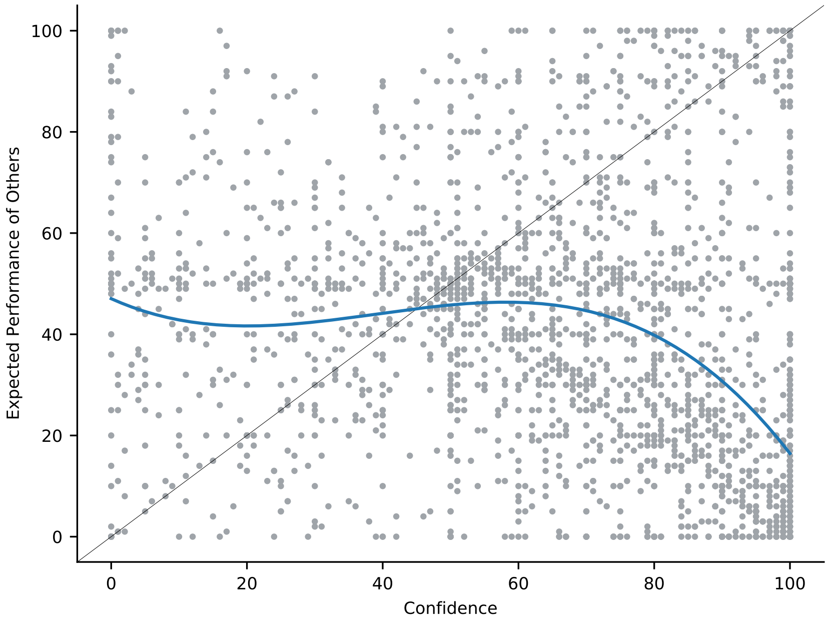


Figure A.2: Scatter plot of $c_{i,i}$ (x-axis) and $c_{i,-i}$ (y-axis), aggregating all tasks. The curve represents a third-degree polynomial fit, minimizing the squared distance between the curve and the set of points.

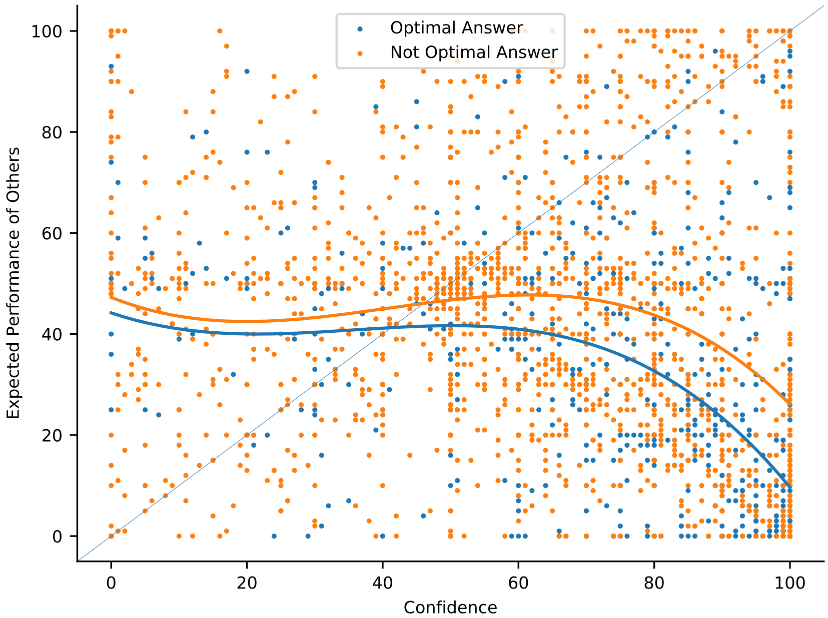


Figure A.3: Scatter plot of $c_{i,i}$ (x-axis) and $c_{i,-i}$ (y-axis), aggregating all tasks. The points are split into two subgroups, depending on whether that participant provided an optimal answer in the pre-learning phase. The curve represents a third-degree polynomial fit, minimizing the squared distance between the curve and the set of points.

A.2 Unweighted Gains and Losses

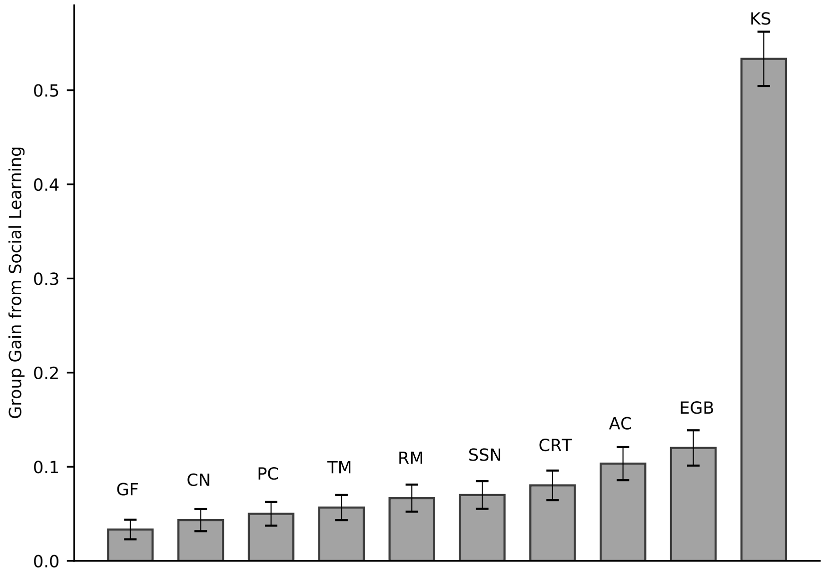


Figure A.4: Unweighted gains, by task. Error bars represent standard errors.

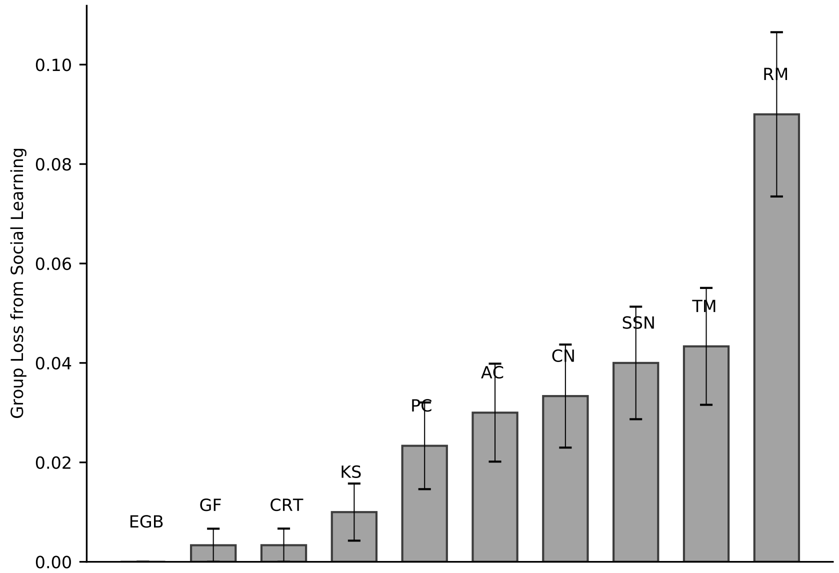


Figure A.5: Unweighted losses, by task (the bar is empty for EGB as there is no loss from social learning for that tasks). Error bars represent standard errors.

A.3 Overlearning and Underlearning

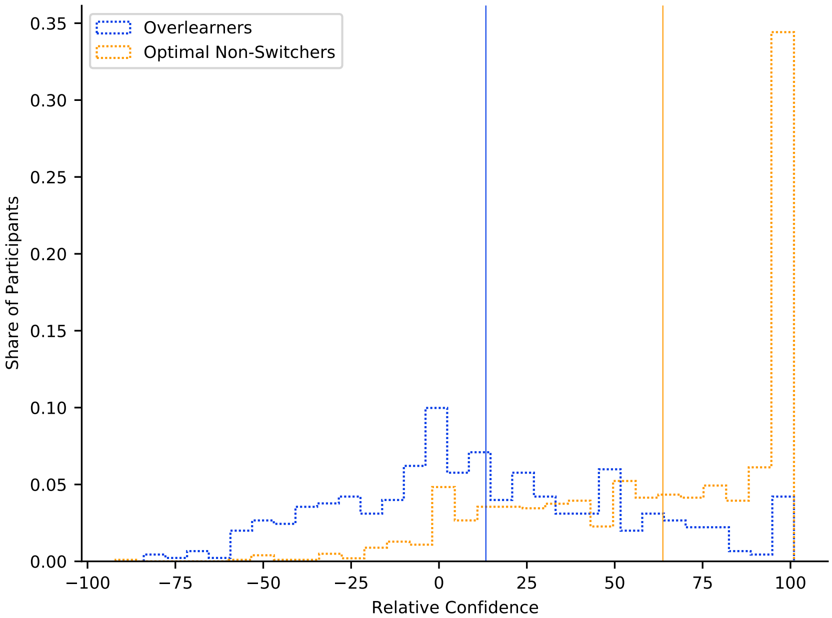


Figure A.6: Relative confidence probability density functions, comparing overlearners and optimal non-switchers. Overlearners are defined as participants who switched despite having picked the optimal action in the first part. Optimal non-switchers are participants who also picked the optimal action in the first part, optimally deciding not to switch in the learning phase.

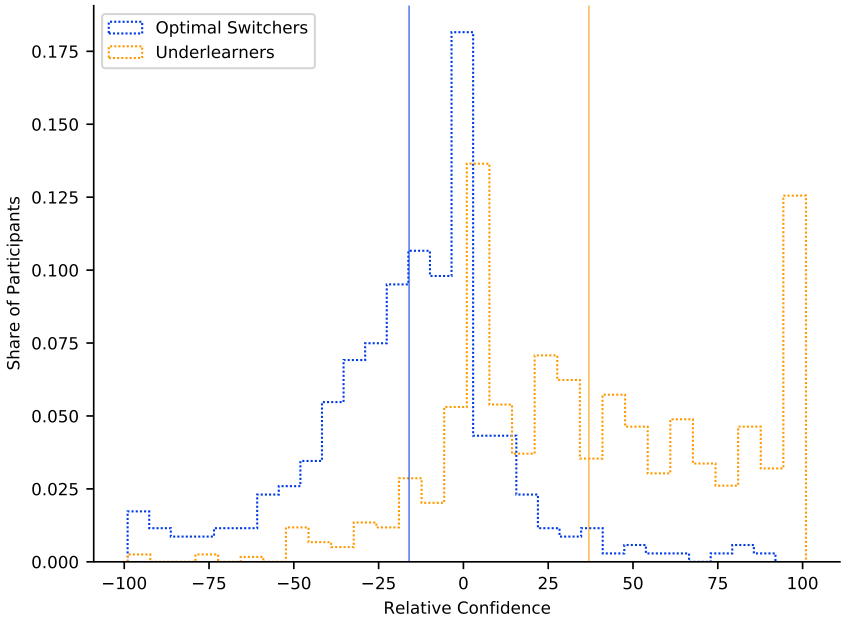


Figure A.7: Relative confidence probability density functions, comparing underlearners and optimal switchers. Underlearners are defined as participants who did not switch despite having picked a sub-optimal action in the first part. Optimal switchers are participants who also picked a sub-optimal action in the first part, optimally deciding to switch in the learning phase.

A.4 Social Learning Impact: Additional Checks

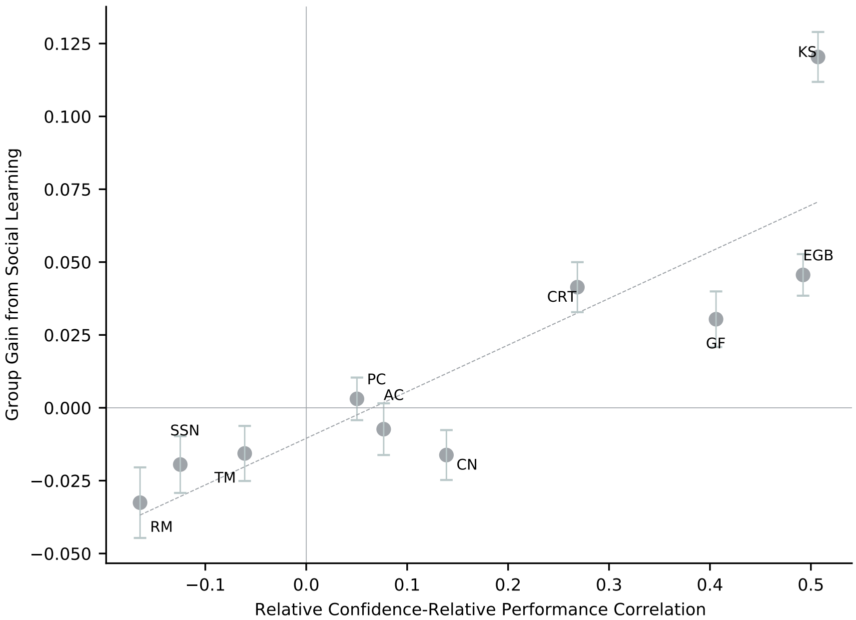


Figure A.8: Scatter plot of relative confidence-relative performance correlation (on the x-axis) and the weighted net gain from social learning (on the y-axis). The error bars represent standard errors. In this case, relative confidence is encoded as a dummy variable, taking the value of 1 if $c_{i,i} > c_{i,-i}$ *and of 0 in the opposite case. Task codes: AC=Acquiring-a-company; CN=Correlation neglect; CRT=Cognitive reflection test; EGB=Exponential growth calculation; GF= Predict sequence of draws; KS=Knapsack; PC=Portfolio choice; RM=Regression to the mean/Attribution; SSN=Account for sample size; TM=Marginal thinking.*

A.5 Answers Distribution

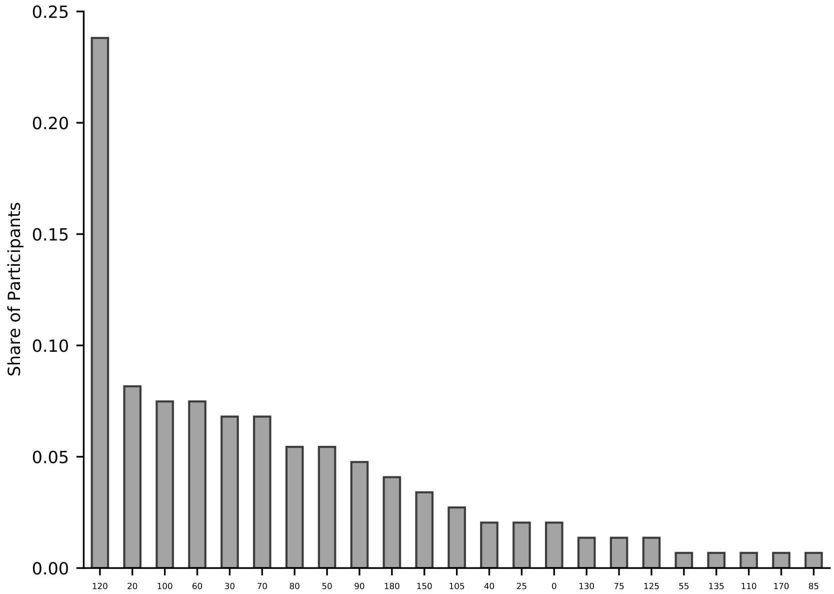


Figure A.9: Distribution of answers, AC.

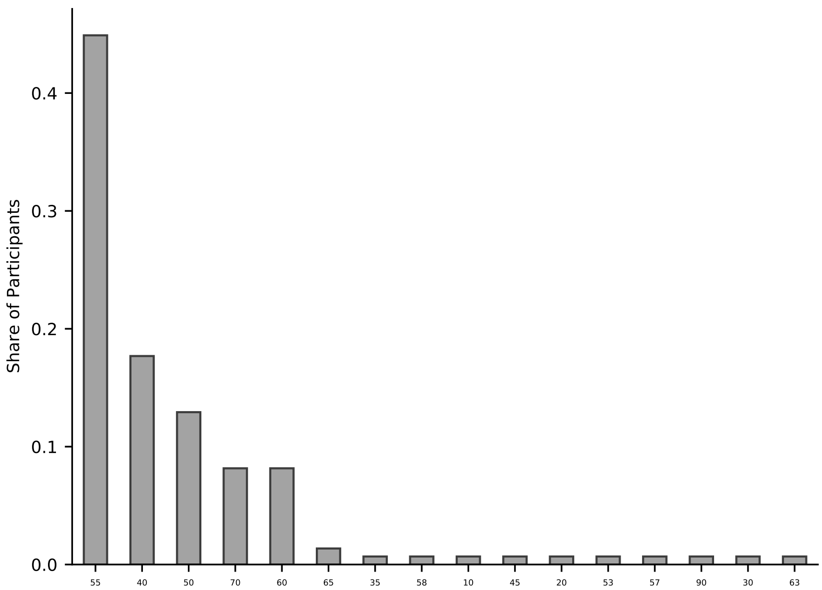


Figure A.10: Distribution of answers, CN.

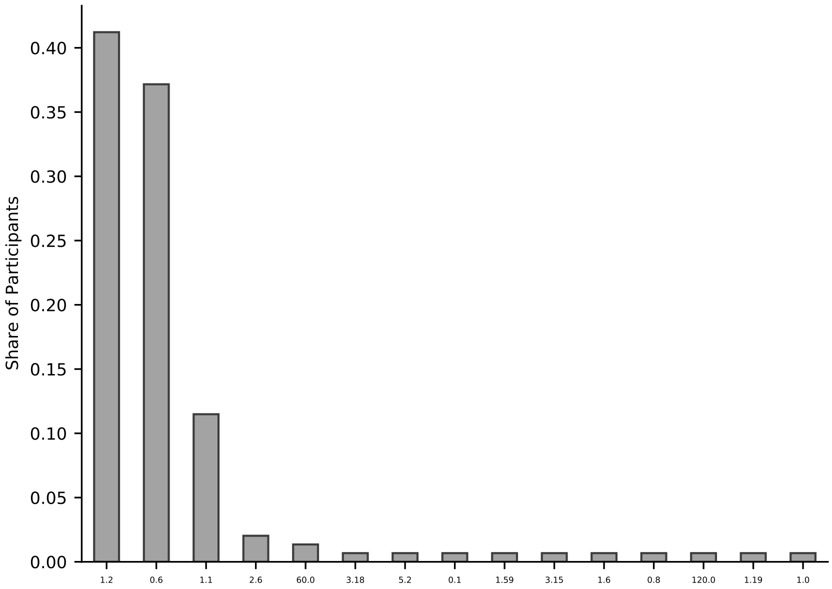


Figure A.11: Distribution of answers, CRT.

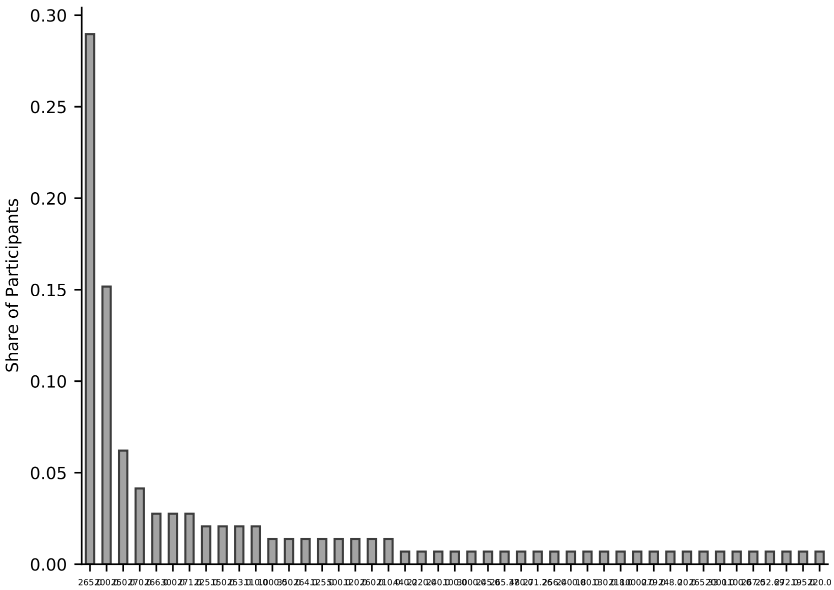


Figure A.12: Distribution of answers, EGB.

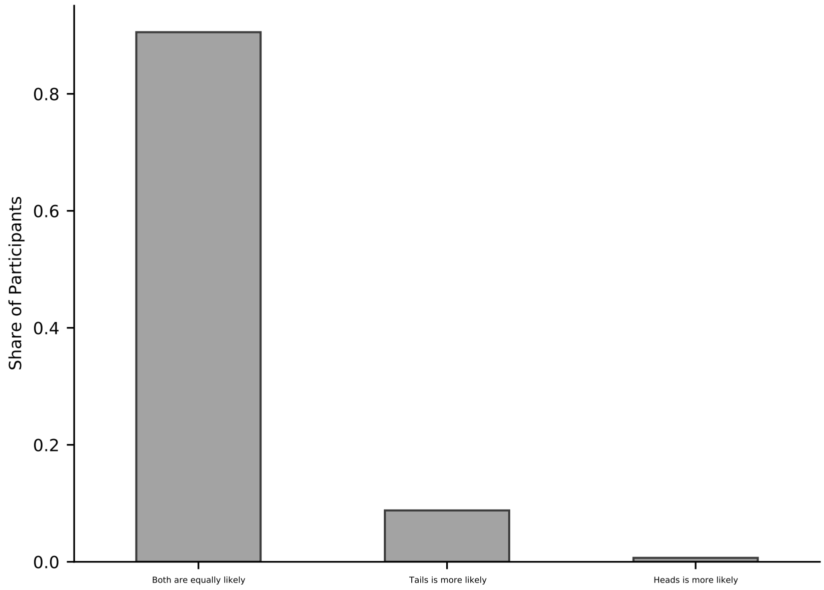


Figure A.13: Distribution of answers, GF.

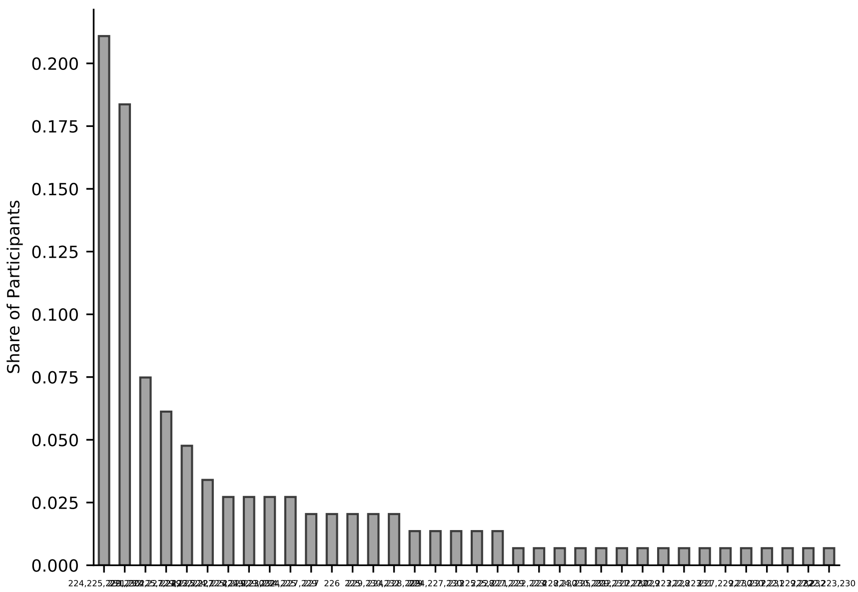


Figure A.14: Distribution of answers, KS.

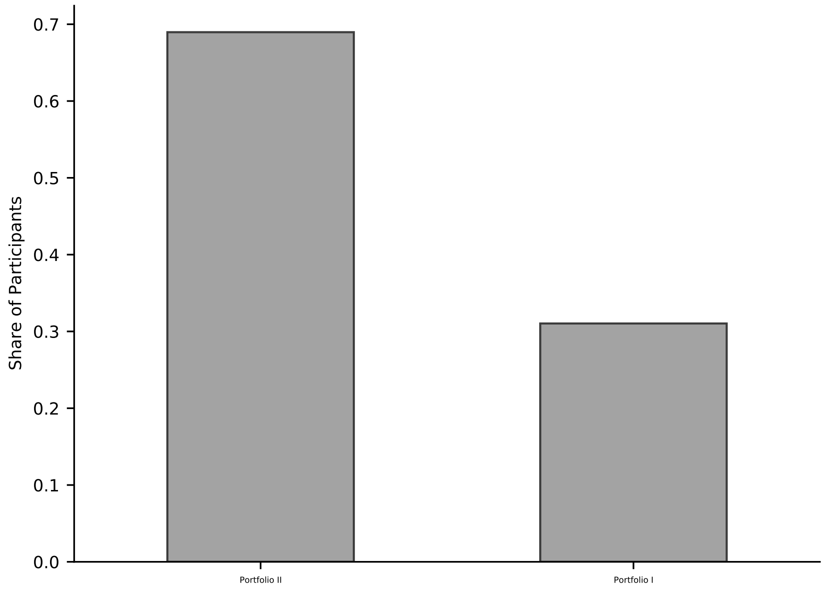


Figure A.15: Distribution of answers, PC.

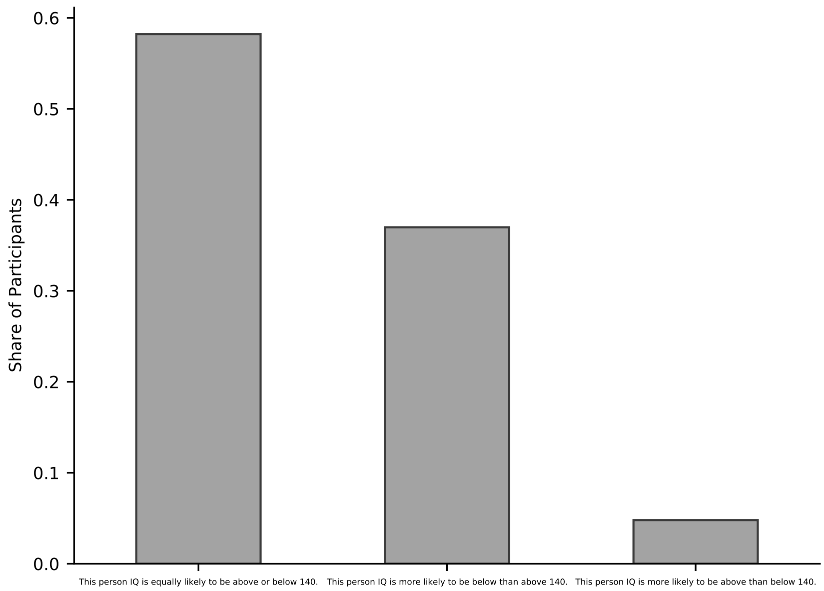


Figure A.16: Distribution of answers, RM.

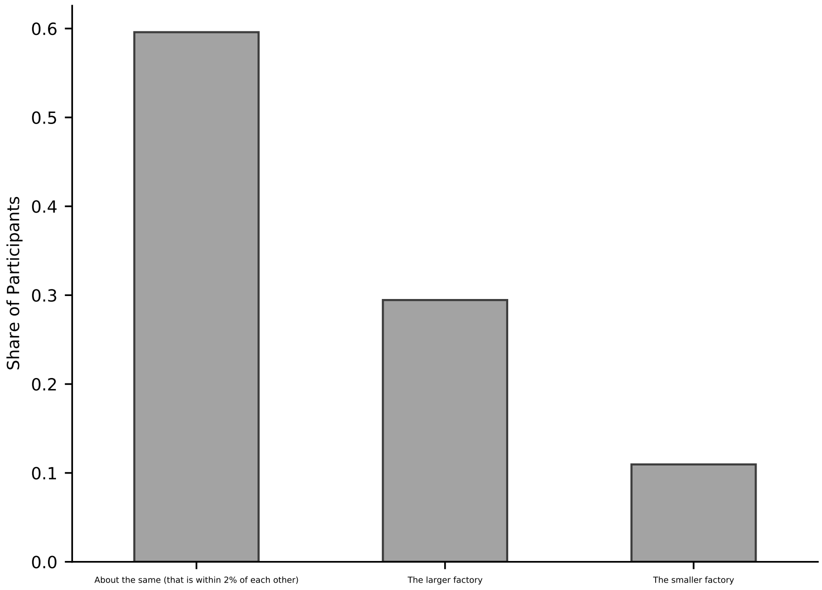


Figure A.17: Distribution of answers, SSN.

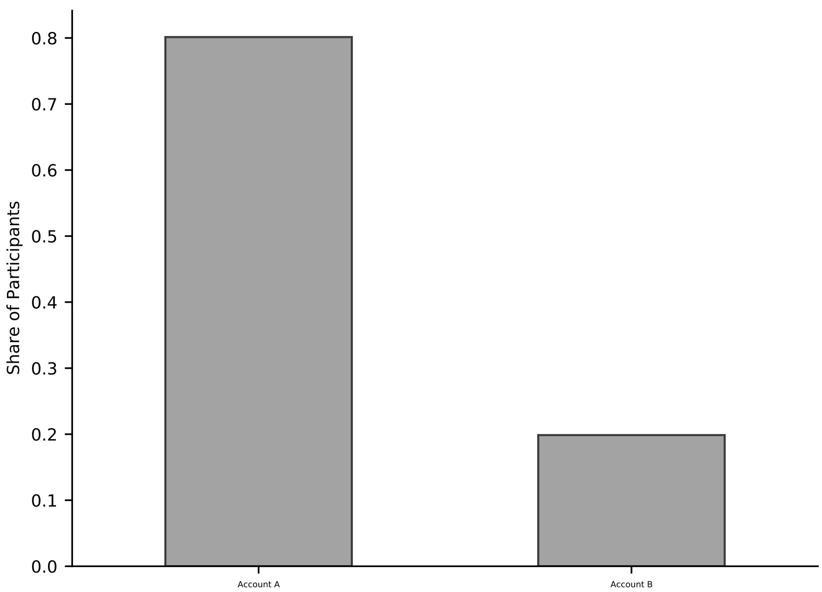


Figure A.18: Distribution of answers, TM.

A.6 Gender Sample Split

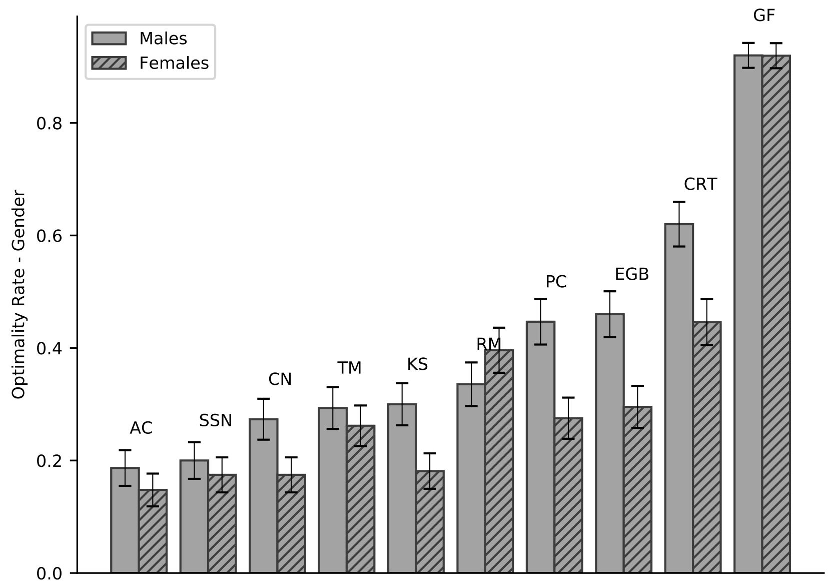


Figure A.19: Share of participants choosing the optimal action, by task and gender. Task codes: AC=Acquiring-a-company; CN=Correlation neglect; CRT=Cognitive reflection test; EGB=Exponential growth calculation; GF= Predict sequence of draws; KS=Knapsack; PC=Portfolio choice; RM=Regression to the mean/Attribution; SSN=Account for sample size; TM=Marginal thinking.

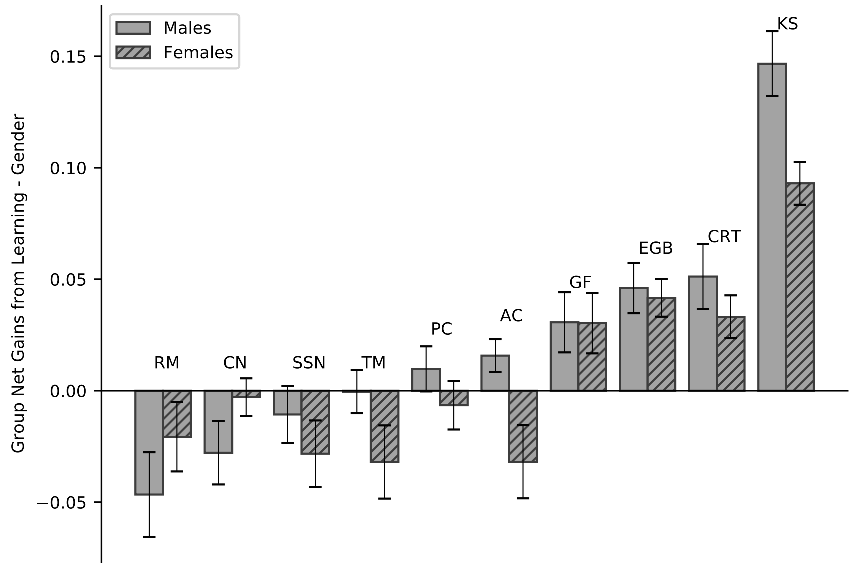


Figure A.20: Group gains from social learning, by task and gender. The weighted net gain measure, for each task, is built by weighting gains and losses with the optimality rate in and its complement on 1, respectively. Error bars represent standard errors. Task codes: AC=Acquiring-a-company; CN=Correlation neglect; CRT=Cognitive reflection test; EGB=Exponential growth calculation; GF= Predict sequence of draws; KS=Knapsack; PC=Portfolio choice; RM=Regression to the mean/Attribution; SSN=Account for sample size; TM=Marginal thinking

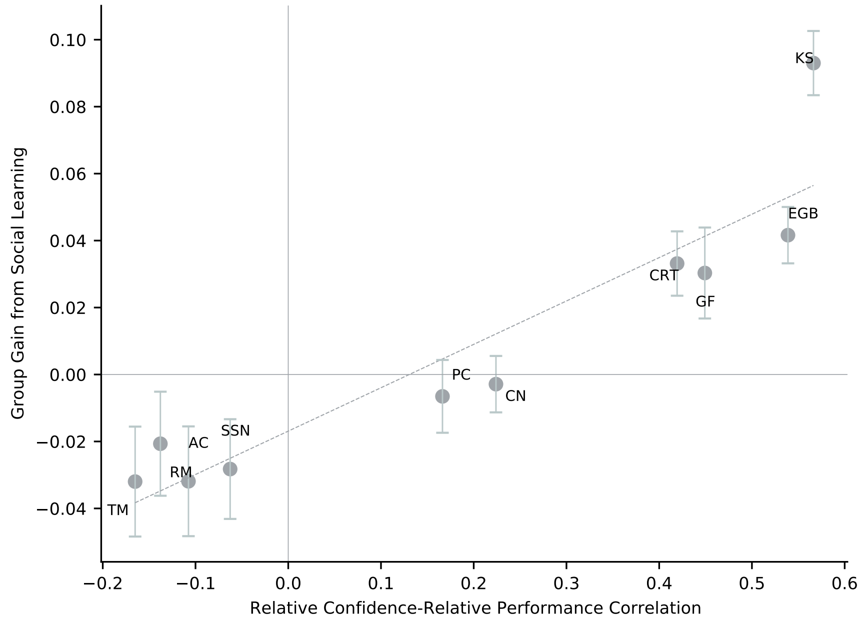


Figure A.21: Scatter plot of relative confidence-relative performance correlation (on the x-axis) and the weighted group gain from social learning (on the y-axis), considering a sub-sample of only female participants. The error bars represent standard errors. Task codes: AC=Acquiring-a-company; CN=Correlation neglect; CRT=Cognitive reflection test; EGB=Exponential growth calculation; GF= Predict sequence of draws; KS=Knapsack; PC=Portfolio choice; RM=Regression to the mean/Attribution; SSN=Account for sample size; TM=Marginal thinking.

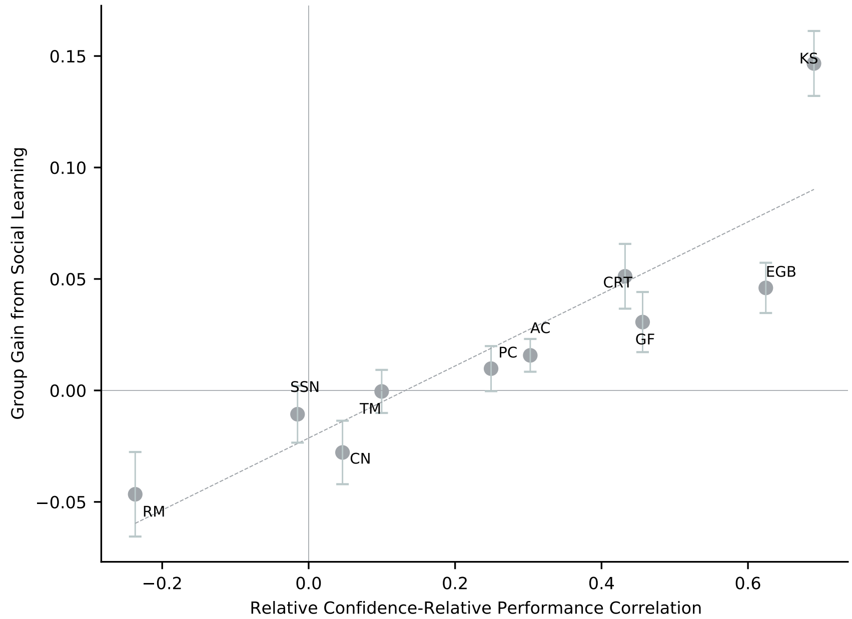


Figure A.22: Scatter plot of relative confidence-relative performance correlation (on the x-axis) and the weighted group gain from social learning (on the y-axis), considering a sub-sample of only male participants. The error bars represent standard errors. Task codes: AC=Acquiring-a-company; CN=Correlation neglect; CRT=Cognitive reflection test; EGB=Exponential growth calculation; GF= Predict sequence of draws; KS=Knapsack; PC=Portfolio choice; RM=Regression to the mean/Attribution; SSN=Account for sample size; TM=Marginal thinking.

A.7 *OtherConf* Condition

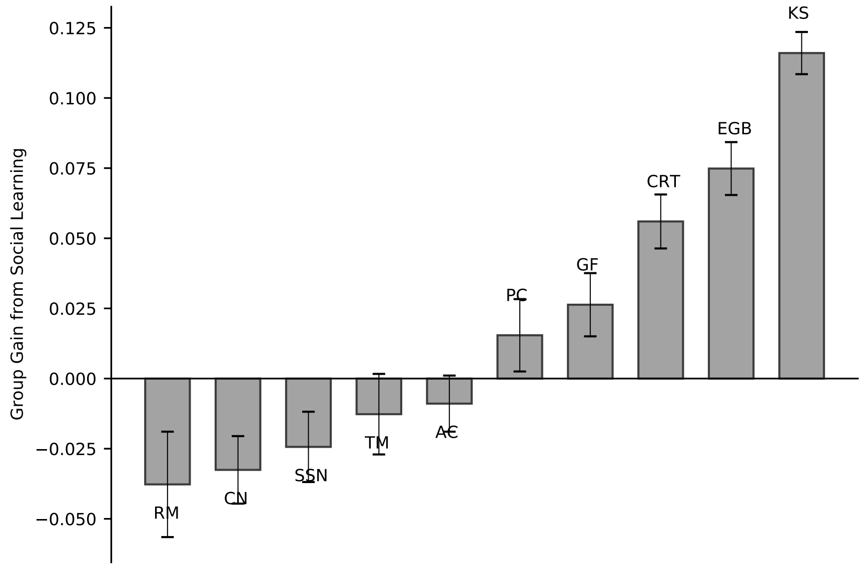


Figure A.23: Group gains from social learning, by task, for the OtherConf condition. The weighted net gain measure, for each task, is built by weighting gains and losses with the optimality rate in and its complement on 1, respectively. Error bars represent standard errors. Task codes: AC=Acquiring-a-company; CN=Correlation neglect; CRT=Cognitive reflection test; EGB=Exponential growth calculation; GF= Predict sequence of draws; KS=Knapsack; PC=Portfolio choice; RM=Regression to the mean/Attribution; SSN=Account for sample size; TM=Marginal thinking

A.8 Robustness

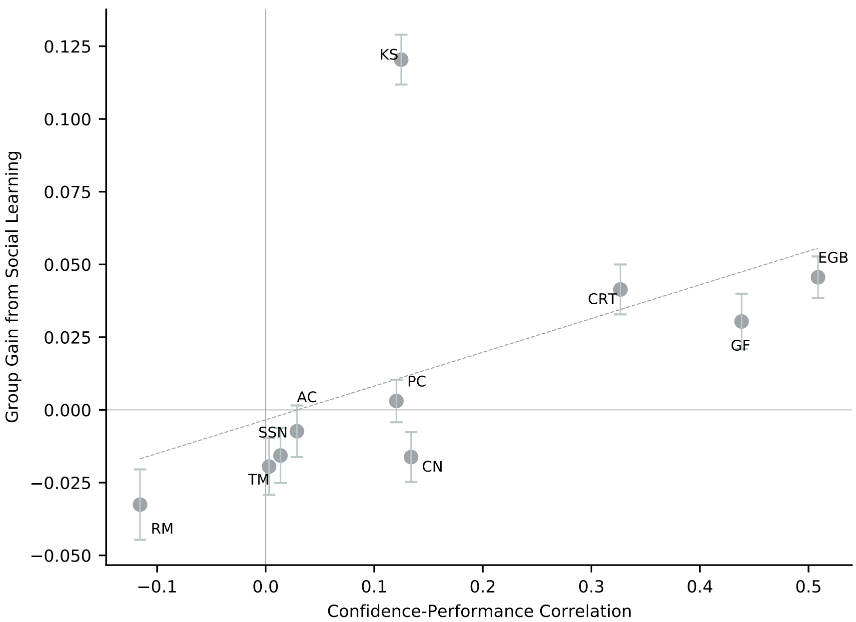


Figure A.24: Scatter plot of confidence-performance correlation (on the x-axis) and the weighted group gain from social learning (on the y-axis). The error bars represent standard errors. Task codes: AC=Acquiring-a-company; CN=Correlation neglect; CRT=Cognitive reflection test; EGB=Exponential growth calculation; GF= Predict sequence of draws; KS=Knapsack; PC=Portfolio choice; RM=Regression to the mean/Attribution; SSN=Account for sample size; TM=Marginal thinking.

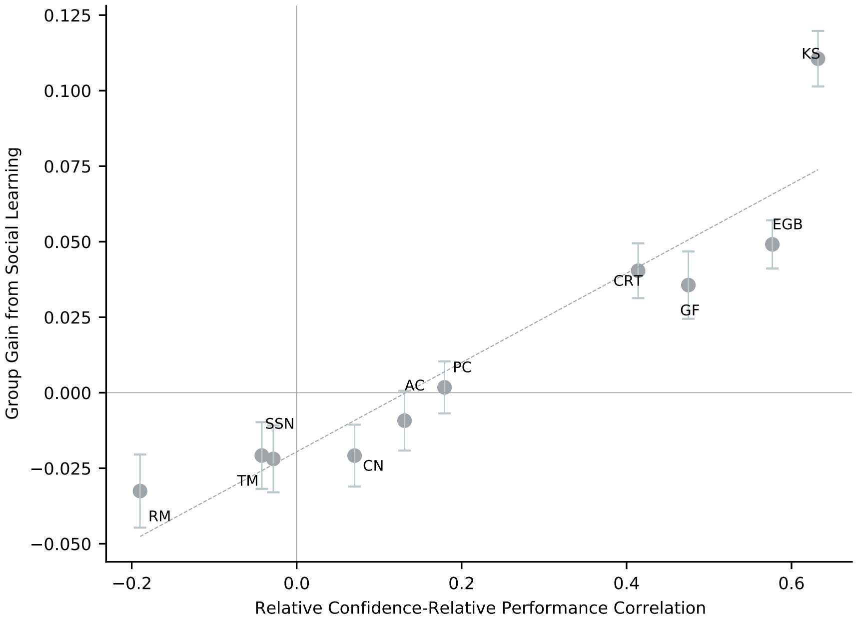


Figure A.25: Scatter plot of relative confidence-relative performance correlation (on the x-axis) and the weighted group gain from social learning (on the y-axis), considering a sub-sample of participants who did not express doubts on the observed actions in an open-ended question at the end of the experiment. The error bars represent standard errors. Task codes: AC=Acquiring-a-company; CN=Correlation neglect; CRT=Cognitive reflection test; EGB=Exponential growth calculation; GF= Predict sequence of draws; KS=Knapsack; PC=Portfolio choice; RM=Regression to the mean/Attribution; SSN=Account for sample size; TM=Marginal thinking.

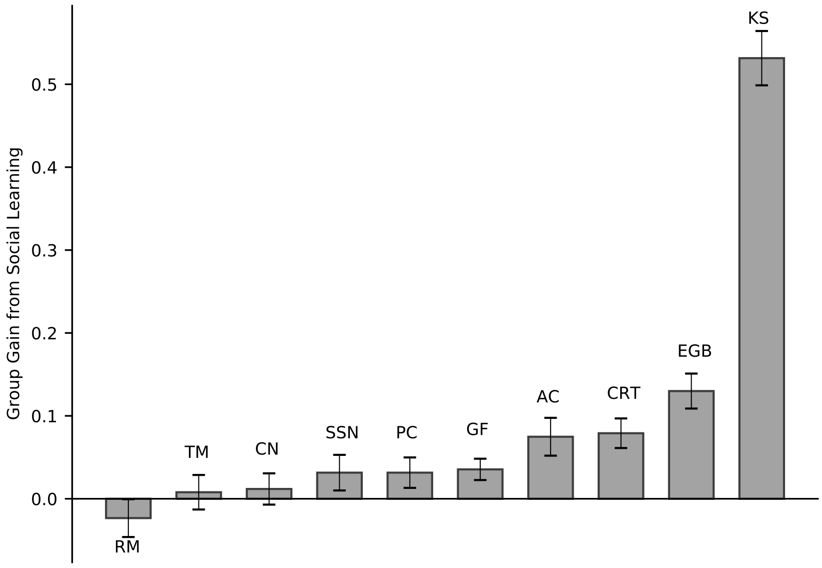


Figure A.26: Group gains from social learning, by task, considering a sub-sample of participants who did not express doubts on the observed actions in an open-ended question at the end of the experiment. The weighted net gain measure, for each task, is built by weighting gains and losses with the optimality rate in and its complement on 1, respectively. Error bars represent standard errors. Task codes: AC=Acquiring-a-company; CN=Correlation neglect; CRT=Cognitive reflection test; EGB=Exponential growth calculation; GF= Predict sequence of draws; KS=Knapsack; PC=Portfolio choice; RM=Regression to the mean/Attribution; SSN=Account for sample size; TM=Marginal thinking

Appendix B Proofs

Proof of Prediction 2 Assume $\beta > 0$, as the opposite case follows with a specular argument. Note that, from (2) and with $\beta > 0$, $c_{i,-i}$ is strictly increasing in p_{-i}. It follows that every agent will assign the highest level of $c_{i,-i}$ to the agent with the highest optimality rate in the set of observable agents. This means that every agent will learn from the same agent, except the second-best-performing agent. For convenience, and w.l.o.g., index the agents such that $p_1 \geq p_2 \geq .. \geq p_N$. The gain from social learning then is:

$$\mathcal{G} = \sum_{i=1}^{N} \gamma\mu_i p_{-i} + (1-\gamma\mu_i)p_i - p_i = \sum_{i=1}^{N} \gamma\mu_i \underbrace{(p_{-i} - p_i)}_{\text{Gain/loss from switching}} =$$

$$= \underbrace{\sum_{i=3}^{N} \gamma\mu_i(p_1 - p_i)}_{\geq 0} + \gamma(p_1 - p_2)(\mu_2 - \mu_1).$$

The first part of the sum is larger than 0 since $p_1 \geq p_i$ for all $i \in \{3, .., N\}$. Hence, a sufficient condition for $\mathcal{G} > 0$ is that $\mu_2 > \mu_1$. Note that μ_i can be rearranged as:

$$\mu_i = \frac{(c_{i,-i})^2}{(c_{i,-i})^2 + c_{i,i}^2} = \frac{c_{i,-i}/c_{i,i}}{c_{i,-i}/c_{i,i} + c_{i,i}/p_e^e{-i}}$$

which is increasing in $c_{i,-i}/c_{i,i}$. In turn, from equation (3) it directly follows that $\frac{\delta c_{i,-i}/c_{i,i}}{\delta p{-i}} > 0$, and $\frac{\delta c_{i,-i}/c_{i,i}}{\delta pi} < 0$ given that $\beta > 0$. Hence, $p_1 > p_2 \implies c_{2,1}/c_{2,2} > c_{1,2}/c_{1,1} \implies \mu_2 > \mu_1$. Finally, μ_i is increasing in β for all i. This implies a higher probability of gains for all agents, except for agent 1. However, the increase in expected gain for player 2 is larger than the increase in expected loss for player 1, as $p_1/p_2 > p_2/p_2$. Hence, $\mathcal{G}$ is increasing in β. $\square$

Appendix C Experimental Instructions

C.1 General Instructions

Instructions (1/4)

Please read the instructions carefully. There will be comprehension checks. If you fail those, you will not be able to participate in the study and get paid.

The study consists of a total of 13 tasks. Each of these tasks consists of four parts:

Part 1**: You will make a decision by answering a question.** Your decision potentially determines your bonus payment. In each question, there is going to be an optimal decision, by which we mean a decision that maximizes your earnings, on average.

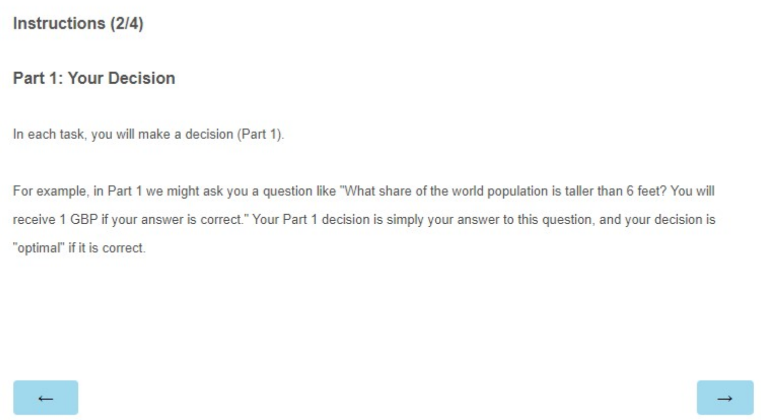
Part 2**: We will ask you how certain you are that your decision in Part 1 was optimal.** Your response to this question does not affect your bonus.

Part 3**: We will show you another participant's answer and ask you about how likely you think the other participant's decision in Part 1 was optimal.** Your response to this question does not affect your bonus.

Part 4**: After observing the answer from another participant you have the chance to change your answer.** As in Part 1, this decision potentially determines your bonus payment.

→

Figure C.1: Instructions screenshot 1



Instructions (2/4)

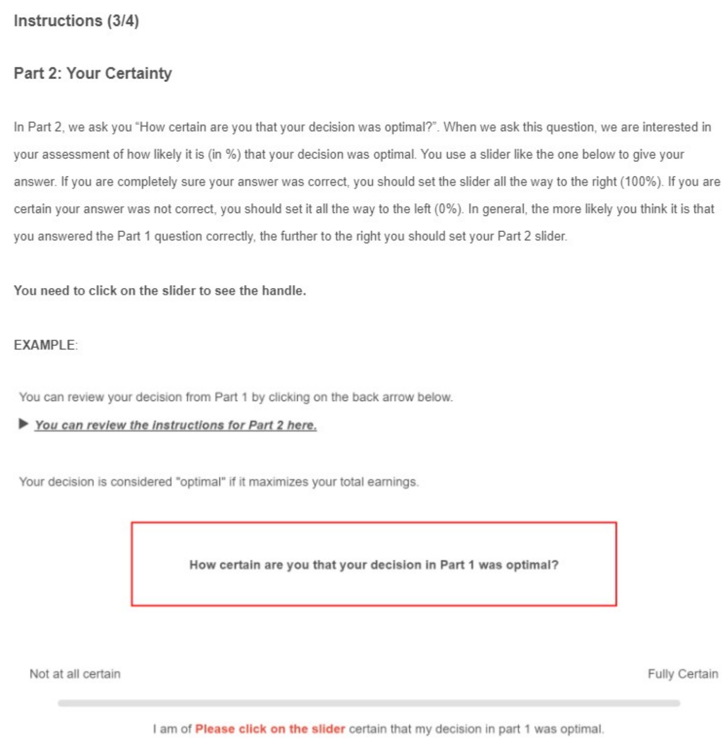
Part 1: Your Decision

In each task, you will make a decision (Part 1).

For example, in Part 1 we might ask you a question like "What share of the world population is taller than 6 feet? You will receive 1 GBP if your answer is correct." Your Part 1 decision is simply your answer to this question, and your decision is "optimal" if it is correct.

← →

Figure C.2: Instructions screenshot 2



Instructions (3/4)

Part 2: Your Certainty

In Part 2, we ask you "How certain are you that your decision was optimal?". When we ask this question, we are interested in your assessment of how likely it is (in %) that your decision was optimal. You use a slider like the one below to give your answer. If you are completely sure your answer was correct, you should set the slider all the way to the right (100%). If you are certain your answer was not correct, you should set it all the way to the left (0%). In general, the more likely you think it is that you answered the Part 1 question correctly, the further to the right you should set your Part 2 slider.

You need to click on the slider to see the handle.

EXAMPLE:

You can review your decision from Part 1 by clicking on the back arrow below.

▶ ***You can review the instructions for Part 2 here.***

Your decision is considered "optimal" if it maximizes your total earnings.

How certain are you that your decision in Part 1 was optimal?

Not at all certain Fully Certain

I am of **Please click on the slider** certain that my decision in part 1 was optimal.

Figure C.3: Instructions screenshot 3

Part 3: Other Participants' Optimality

In Part 3, we show you another participant's answer to the **exact same question** and ask you "How likely do you think this participant's answer is optimal?". When we ask this question, we are interested in your guess of the probability that the shown answer is optimal. In general, the more likely you think it is that the shown answer is correct, the further to the right you should set your Part 3 slider.

You need to click on the slider to see the handle.

EXAMPLE:

A decision is considered "optimal" if it maximizes total earnings.

How likely do you think this participant's answer is optimal?

Extremely Unlikely | Extremely Likely

It is **Please click on the slider** likely that this participant's answers is optimal.

← →

Figure C.4: Instructions screenshot 4

Instructions (4/4)

Part 4: Review the Answer

In Part 4, you can compare your answer and the other participant's answer and may switch, if you wish to do so. Remember that you should always pick the answer that you think has a higher probability of being correct to maximize the chances of receiving the bonus.

Bonus Payment

One of the 13 tasks will be randomly drawn to be relevant for a bonus payment of 0.5 £. Similarly, for that task, either Part 1 or Part 4 answer may matter for your bonus payment, with the same probability. **You don't know which answer in which task is relevant for your bonus, so you should simply always take the decision you think is best.** You receive the bonus if your answer in the relevant decision is optimal.

By clicking the next arrow you will be redirected to comprehensions checks.

← →

Figure C.5: Instructions screenshot 5

C.2 Comprehension Checks

How is your bonus determined?

- I will go through 10 tasks. In each tasks there are 4 parts, of which Part 1 and Part 4 may be relevant for my bonus payment. One of this 20 decisions is randomly selected and I obtain the bonus if it corresponds to the optimal decision.
- I will go through 10 tasks. Part 1 and Part 4 may be relevant for my bonus payment and each Part of each task will get paid.

Suppose you DID take the optimal decision in Part 1. Which Part 2 decision would be more reflective of your actual performance?

- If I stated that I am 80% certain I got the task right
- If I stated that I am 30% certain I got the task right

Suppose that you think that the other participant did NOT take the optimal decision in Part 1. Which Part 3 decision would be more reflective of their actual performance?

- If I stated that I think it is 70% likely that they got the task right
- If I stated that I think it is 20% likely that they got the task right

Which of the following statements is true?

- In Part 4 I am free to either change my answer or to stick with my initial one
- I have to change my initial answer in Part 4

Figure C.6: Comprehension Questions.

C.3 Tasks

Part 1: Your Decision

- You have a budget of 180 points. You can either keep it or use it to buy a company.
- Bob is selling his company. The **VALUE** of Bob's company to him is either **20** or **120 points**, but you do not know which. There is a **50% chance** it is worth 20 points to him and a 50% chance it is worth 120 points to him.
- **Bob's company has a higher value to you than to Bob.** If you acquire his company, it will pay you 1.5 times its value to Bob. Therefore, if the value of the company turns out to be 20 points for Bob, it would be 30 points for you. If the value of the company turns out to be 120 points for Bob, it would be 180 points for you.
- The realized value is determined randomly by the computer, and you will not know the value until after you've made your decision
- You can make a **PRICE** offer to Bob of up to 180 points
- Your earnings will be determined as follows:
  - If you offer a PRICE **that is at least as high** as Bob's realized VALUE, Bob will accept your offer, and your earnings will be *Earnings = (Your budget) + 1.5* (Bob's* ***VALUE****) - (the* ***PRICE*** *you offered)*
  - If you offer a PRICE **less** than Bob's realized VALUE, you will not acquire his company and your profits will be EARNINGS = Your Budget

We will pay you £0.5 if your answer corresponds to the optimal bid and substract a pence for every point you are away from the correct answer.

How many points do you bid for Bob's company?

→

Figure C.7: Acquiring a Company (AC) instructions.

Part 1: Your Decision

- There are three people: Mary, David and John. Each of them is interested in estimating the weight of a water bucket in pounds.
- Mary and David both **get to take a peek at the bucket**. They are equally good at estimating weight. Each of them gets weight estimates right, on average, but sometimes makes **random mistakes**. Mary and Davide are equally likely to make mistakes in any given estimate they make.
- Mary and David both share their estimates with John, who has never seen the bucket. Because he has never seen the bucket, John computes his best estimate of the weight of the bucket as the average of the estimates of Mary and David.
- **You have never seen the bucket either, but you're asked to produce an estimate of its weight**. You now talk to Mary and John. They share the following estimates with you:
    - Mary's estimate: 70
    - John's estimate: 40
- Your task is to estimate the weight of the bucket.
- We will pay you more points the closer your decision is to the statistically-correct estimate given the information you are provided.
    - Specifically, we will pay you 0.5£ if your decision corresponds to this correct answer. We subtract 1 pence for every number you are away from the correct answer.
    - You cannot make losses, meaning you always earn at least 0 pence.

What is your best estimate of the weight of the bucket?

→

Figure C.8: Correlation Neglect (CN) instructions.

Part 1: Your Decision

Milk and a cookie cost **GBP 3.20 in total**. Milk costs **GBP 2 more** than the cookie. **How many GBP does the cookie cost?**

→

Figure C.9: Cognitive Reflection Test (CRT) instructions.

Part 1: Your Decision

- **Suppose a stock starts at a value of $100.**
- **It grows by 5% each year relative to its beginning-of-year value.**
- **How much is it worth after 20 years?** If necessary, round your decision to the nearest dollar value.
- We will pay you more points the closer your decision is to the correct answer.
  - Specifically, we will pay you £0.5 and substract from this in quarter pence the absolute difference between your decision and the correct stock value. For example, if the absolute difference between the true stock value and your decision is 20$, we will substract 5 pence and you will earn £0.45.
  - You cannot make losses, meaning you always earn at least £0.

How much $ is the stock worth after 20 years? (round to the nearest integer)

→

Figure C.10: Exponential Growth Bias (EGB) instructions.

Part 1: Your Decision

Imagine you are tossing a **fair coin**. After eight tosses you observe the following result. (where **T** stands for **TAILS** and **H** stands for **HEADS**):

T - T - T - H - T - H - H - H

We will pay you £0.25 if your decision corresponds to the statistically-correct option given the information you are provided, and nothing otherwise.

Which event is more likely to happen on the next coin toss?

- Heads is more likely
- Tails is more likely
- Both are equally likely

→

Figure C.11: Gambler's Fallacy (GF) instructions.

Part 1: Your Decision

- There are 12 **Items** shown in the Table below. Your task is to choose one or more of these items
- Each item has a **VALUE** in pence to you. Your earnings for this task are given by the **SUM OF VALUES** you choose.
- However, each item also has a **WEIGHT**. The total **SUM OF WEIGHTS** of the items you choose **CANNOT EXCEED 14**. If your selection exceeds this weight limit, you will earn nothing.

Which items do you choose? (Please click on the columns)

Current sum of weights chosen: 0

Value	2	3	4	5	6	9	8	7	6	5	8	9
Weight	3	4	6	3	5	13	6	9	2	4	7	7

→

Figure C.12: Knapsack (KS) instructions.

Part 1: Your Decision

- **In this task, you'll be asked to choose an investment portfolio that consists of different stocks.**
- There are **four stocks** that pay you different amounts of money depending on the color of a ball that a computer will randomly draw. Each of the colors red, blue and green is equally likely to get by the computer.
- The table below shows you the **payment rate** of each stock, depending on which ball the computer randomly draws. For example a realized return of 10 % means that if you invest 20 points, you end up with 22 points. Likewise, a realized return of -10% means that if you invest 20 points, you end up with 18 points.

Color of ball drawn	Return of Stock A	Return of Stock B	Return of Stock C	Return of Stock D
Red	13%	-2%	-9%	17%
Blue	-8%	8%	12%	-9%
Green	8%	6%	7%	7%

- In total, you need to invest 100 pences across these stocks. You can select one of the portfolios (combinations of stock purchases) below.
- The computer will randomly draw a ball and pay you the total amount of pences earned across the stocks in your portfolio.

Portfolio	Points in Stock A	Points in Stock B	Points in Stock C	Points in Stock D
I	50	25	0	25
II	25	25	25	25

Which investment portfolio do you choose ?

Portfolio I

Portfolio II

→

Figure C.13: Portfolio Choice (PC) instructions.

Part 1: Your Decision

- The **average** score on a standard **IQ test** is **100.** Suppose a **randomly** selected individual obtained a score of **140**.
- Suppose further that an IQ score is the sum of both **true ability** and **random good or bad luck.** The luck component can be positive or negative but equals zero on average (over all people).

Which of the following statements is correct?

This person IQ is more likely to be above than below 140.

This person IQ is equally likely to be above or below 140.

This person IQ is more likely to be below than above 140.

→

Figure C.14: Regression to the Mean (RM) instructions.

Part 1: Your Decision

- There are **two factories** that make office chairs. The **larger** factory produces **45 chairs** each day, and the **smaller** factory produces **15 chairs** each day.
- For both factories, there is a **10% random chance** that any given chair is defective. However since this is random, the exact percentage varies from day to day. Sometimes it may be higher than 10%, sometimes lower.
- For a period of 1 year, each factory recorded the days on which **MORE THAN 20%** of the chairs were defective.

We will pay you £0.5 if your decision corresponds to the statistically-correct option given the information you are provided, and nothing otherwise.

Which factory do you think recorded more days on which more than 20% of the chairs were defective ?

The larger factory

The smaller factory

About the same (that is within 2% of each other)

→

Figure C.15: Sample Size Neglect (SSN) instructions.

Part 1: Your Decision

- You are given 100 points (money) to Store in two different **BANK ACCOUNTS**, A and B. Points Stored in each account are **TAXED** by the government in different ways. You can store your points in 20-unit increments.
- Here is how much you pay in taxes for account A based on the total amount stored:

Investment in account A (in Points)	20 total points stored	40 total points stored	60 total points stored
Total taxes to be paid for account A (in points)	4	12	24

- For instance, if you store 20 points in account A, you pay 4 points, leaving you with 16 points in account A after taxes. If you store 40 points, you pay 12 points in taxes, leaving you with 28 points in account A after taxes, etc.

- Here is how much you pay in taxes for account B based on the total amount stored:

Investment in account B (in Points)	20 total points stored	40 total points stored	60 total points stored
Total taxes to be paid for account B (in points)	10	20	30

- For instance, if you store 20 points in account B, you pay 10 points in taxes. leaving you with 10 points in account B after taxes. If you store 40 points, you pay 20 points in taxes, leaving you with 20 points in account B after taxes, etc.
- In total, you can put 100 points into the bank.
  - We already put 40 points into bank account A for you,
  - We also put another 40 points into account B for you
  - You now have an **ADDITIONAL** 20 points to put into the bank. You must now decide into which account you would like to put these last 20 points.
- We will pay you £0.5 for the 100 points in the bank, minus total taxes from accounts A and B (That is, we deduct a quarter pence for every point of taxes).

Into which account do you put your additional 20 points?

Account A

Account B

→

Figure C.16: Thinking at the Margin (TM) instructions.

C.4 Tasks Description Table

Table C.1: Task Description (adopted from Enke et al. 2022)

Task	Short Description	Common Wrong Answer	Correct Answer
Correlation neglect (CN)	Enke and Zimmermann (2019) show how people often fail to take into account the correlation among information sources when updating beliefs. Following their setup, two hypothetical characters, Ann and Bob, estimate the weight of a bucket. A third hypothetical character, Charlie, computes the average of the two guesses. The participant is asked to give his estimate for the weight of the bucket, being presented with Charlie's estimate of 40 and Ann's estimate of 70.	55	40
Sample size neglect (SSN)	When asked to judge the probability of obtaining a sample statistic, subjects often fail to take the sample size into account ("Law of small numbers" (Kahneman & Tversky, 1972)). Subjects are presented a version of the their "hospital problem", in which they are asked whether a factory that produces 45 chairs each day or a factory that produces 15 chairs each day has more days on which more than 20 % of chairs are defective.	Equally likely	More likely in the smaller factory

lename C.1 – continued from previous page

Task	Short Description	Common Wrong Answer	Correct Answer
Regression to the mean/ misattribution (RM)	Outcomes are often attributed to internal factors rather than to random noise (Failure to account for mean reversion (Kahnemann and Tversky, 1973)). In the task subjects are asked to state whether the true IQ of a hypothetical test-taker is more likely to be above or below 140, given that their IQ test score is 140, the average population score is 100, and the additional information that test scores reflect a combination of true IQ and random noise.	True IQ is equally likely to be above or below 140	True IQ is more likely to be below than above 140
Acquiring-a-company (AC)	Reflecting a class of errors in contingent reasoning the Acquiring-a company-game is studied with respect to many applications in economics. In this version of the task, a hypothetical seller has a company that is worth either 20 or 120 points to him. The company's value to the buyer is 1.5 times higher as the value to its seller. The subject proposes a take-it-or leave it offer, which the seller accepts if the offer is at least as high as the value of the company to him.	> 20	20

lename C.1 – continued from previous page

Task	Short Description	Common Wrong Answer	Correct Answer
Cognitive Reflection Test (CRT)	The CRT is widely used to capture the tendency of a subject to correct his intuitive but wrong "System 1" responses by engaging in further reflection. Here subjects were presented the question "Milk and a cookie cost GBP 3.20 in total. Milk costs 2 GBP more than the cookie. How many GBP does the cookie cost ?"	1.20 GBP	0.6 GBP
Knapsack (KS)	Past experiments have shown that people often fail to identify the value-maximizing bundle when facing a constrained optimization problem. In this task subjects were presented a set of 12 items, each containing a value and a weight. They were then asked to pick items from that set to maximize the value of the items, while satisfying a constraint on the weights.	-	-
Portfolio Choice (PC)	The 1/N heuristic (Benartzi and Thaler, 2001) according to which investors split their investments equally across all available assets is one example for well documented failures of people to construct efficient portfolios. In the task subjects are to choose between two portfolios consisting of four assets each. The portfolios are constructed such that the one which allocates 1/4 of the budget to each asset is strictly dominated by the other available portfolio.	1/N portfolio	-

lename C.1 – continued from previous page

Task	**Short Description**	**Common Wrong Answer**	**Correct Answer**
Thinking at the margin (TM)	One of the main economic principles of rational decision making involves thinking at the margin rather than thinking in averages. Yet, previous studies have shown that people are consistently inclined to think in terms of averages. Using an adapted version of Rees-Jones and Taubinsky's (2020) taxation problem, subjects are required to decide into which of two bank accounts with different average and marginal tax rates they should allocate 20 points.	Bank account with the lower average tax rate	Bank account with the lower marginal tax rate
Exponential Growth bias (EGB)	Many people consistently tend to perceive a growth process as linear when, in fact, it is exponential. EGB is exhibited in numerous decision contexts such as exponential time discounting, savings and investment. Subjects are asked to guess what the value of a stock that is worth 100 GBP today will be in 20 years if its value increases by 5 % each year.	200 GBP	265 GBP