Information Processing: The Role of Expertise within Peer Effects

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ABSTRACT

We experimentally examine the mechanisms underlying peer effects in financial markets. We hypothesize that individuals are not too confident about how to process information regarding financial markets and thus look among their peers for someone who is more capable in processing the information - an expert. Our experimental evidence supports this hypothesis: Subjects with lower confidence in their decisions follow their peers more often and peers with higher expertise are followed more often. In our experimental design peers do not possess additional information to ensure that our results are driven by the ability to process common information. We therefore introduce a new channel to the peer effects literature - information processing.

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1 Introduction

Making financial decisions is a difficult task. Individuals are usually confronted with many alternatives, which might comprise jargon and unfamiliar concepts. Since most people are not trained for this task, they look for guidance within their social environment. They talk to their relatives, friends, and colleagues – their peers – before making a decision (Ellison & Freudenberg, 1995). As such, the individuals' decisions might correlate with the decision of their peers, so called peer effects (Cooper & Rege, 2011).

We present a new channel capable of explaining why individuals follow their peers while peers cannot serve as source of additional information: information processing. We hypothesize that individuals are not too confident about how to *process* information regarding financial markets and search for references among their peers. They therefore look for those peers, who are the most capable in processing the information - experts[1]. Our hypothesis predicts a positive relation between individuals' perceived relative expertise of their peers and the strength of peer effects. Vice versa, peer effects should be weaker for individuals with higher confidence in their own ability to process information.

To test our prediction, we employ an experimental setting. This allows us to rule out that peer effects occur because peers possess additional information and facilitates a clean examination of the information processing channel. Moreover, experimental analyses overcome the identification issue inherent in the study of peer effects outlined by Manski (1993). The experiment comprises three parts. First, subjects must answer seven questions related to statistics and probability calculation to endogenously determine expertise within the experiment. Second, subjects are repeatedly faced with a typical bookbag-and-pokerchip task. They are asked to provide their probability estimate that a fictional stock is in the good (instead of the bad) state based on observed price signals to resemble financial markets. Subjects are then presented with a randomly allocated peer's estimate on the same task and

[1] Social psychologists report that people imitate the actions of those who appear to have expertise (see Bikhchandani, Hirshleifer, and Welch (1998)).

have the chance to adjust their initial estimate. In the treatment group subjects are also provided with the number of correctly answered expert questions by the peer to form beliefs about the peer's expertise. Third, subjects must answer a brief demographic survey.

We find that perceived relative expertise, measured as the difference of the peer's and the subject's number of correctly answered statistics and probability calculation questions, has a positive impact on the subject's adjustment decisions. A one-point higher difference in the number of correctly answered questions leads to a 3% higher likelihood of making an adjustment after the initial estimate. Similarly, the likelihood of switching to the peer's estimate compared to sticking to the own initial estimate increases with the difference in correctly answered questions. Confidence in the initial estimate on the other hand leads to fewer adjustments. On a seven-point scale, a one point higher self-reported confidence reduces the likelihood of making an adjustment by 4%. Similarly, the likelihood of switching to the peer's estimate compared to sticking to the own initial estimate decreases the higher the self-reported confidence. These effects are non-linear. The impact of confidence is strongest for subjects who have high confidence and who observe peers with high relative expertise, whereas the impact of perceived relative expertise is strongest for subjects who have low confidence and who observe peers with low relative expertise. Conditional on making an adjustment, the magnitude of the adjustment increase with perceived relative expertise as well. Confidence, however, does not seem to affect the magnitude of the adjustment. Information regarding the peer's estimate is beneficial for the subjects. Observing the peer's estimate increases the subjects' confidence in their own estimate and adjusting their initial estimate raises the likelihood of providing a correct estimate by one third.

While peer effects have been studied extensively in the field of finance[2], the largest part of this literature focuses on social learning, i.e. situations in which the social network serves as a source of information (Kuchler & Stroebel, 2021). The literature distinguishes two channels of social learning: information diffusion and observational learning. Information

[2] See for example Lerner and Malmendier (2013); Ahern, Duchin, and Tyler (2014); Beshears, Choi, Madrian, and Milkman (2015); Hong, Kubik, and Stein (2005a); Li (2003); Ivković and Weisbenner (2007); Hong, Kubik, and Stein (2005b).

diffusion refers to the transmission of information among peers[3]. Observational learning is about observing the peers' decisions which in turn reveal information to the individuals[4]. Both channels have in common that the peers possess information on top of the individuals' information: in the information diffusion channel additional information travels through the social network to the individuals; in the observational learning channel the individuals infer additional information from their peers' decisions.

It is rational for individuals to incorporate the information provided by peers through either channel since it expands their information set, resulting in peer effects. However, there is no rational benchmark if the peer does not possess additional information. As such, it is not clear whether and why individuals follow their peers in scenarios without additional information.

There are a few studies which try to explain peer effects by social interaction, arguing that peer choices directly influence individuals' utility (Kuchler & Stroebel, 2021). The most studied channel in this stream of literature is conformity, an intrinsic preference to conform with peers[5], and produces mixed evidence [6]. Cooper and Rege (2011); Lahno and Serra-Garcia (2015); and Frydman (2015) find that social regret respectively envy can explain peer effects. As another alternative channel Bursztyn, Ederer, Ferman, and Yuchtman (2014) propose social utility through possession, claiming that individuals' utility increases when they possess the same item as their peers, for example because they can talk about it.

We introduce information processing as a new channel to the peer effects literature. This channel is not about additional information, but about the processing of common information. Individuals look for reference among their peers and search for those who are the most capable in processing the information. Since individuals infer from their peers'

[3] Duflo and Saez (2003); Cai, De Janvry, and Saoulet (2015); and Brown, Ivković, Smith, and Weisbenner (2008), for example, find evidence supporting this channel. Conlon, Mani, Rao, Ridley, and Schilbach (2022) show, however, that individuals are much less sensitive to information discovered by others compared to information discovered by themselves.

[4] This channel goes back to Banerjee (1992); Bikhchandani, Hirshleifer, and Welch (1992); and Welch (1992) who theoretically study informational cascades. Anderson and Holt (1997) transfer the idea of informational cascades to the laboratory and Avery and Zemsky (1998); Drehmann, Oechssler, and Roider (2005); and Cipriani and Guarino (2005) relate it to financial markets.

[5] See Sherif (1937); Asch (1951, 1958); Bernheim (1994).

[6] See e.g., (Lahno & Serra-Garcia, 2015; Goeree & Yariv, 2015; Corazzini & Greiner, 2007).

decisions how common information should be processed, their social network still serves as a source of information. Individuals' utility, however, is not directly affected by this channel. As such, we consider information processing to be part of the social learning strand of the literature, not social interaction.

In addition, we provide evidence that peer expertise matters for peer effects, thereby showing which kind of peers are important and thus contributing to the research agenda in social finance defined by Kuchler and Stroebel (2021). So far, the only finding in this direction stems from Bursztyn et al. (2014) who identify heterogenous learning effects in line with our hypothesis: unsophisticated individuals react more strongly to others' decisions and sophisticated individuals' decisions have a greater impact on others. The authors admit, however, that their sample size for this analysis is very small and therefore must be viewed with caution. We are thus the first to provide powerful evidence showing that peer expertise matters and has a positive impact on peer effects.

Falk and Zimmermann (2018) find that commitment to an opinion reduces the willingness to incorporate additional information. In their experiments subjects commit to their guess of the number of peas in a bowl by writing it down and handing it to the experimenter. Similarly, subjects in our experiment commit to their estimate using the slider. We thus show that perceived relative expertise of the peer negatively scales the effect of commitment.

The paper proceeds as follows: in Section 2, we describe the experimental design in detail; in Section 3, we develop a framework to derive our hypotheses; in Section 4, we define the empirical specifications and present the experimental results; and in Section 5, we provide our conclusion.

2 Experimental Design

The experiment consists of three parts. In the first part, subjects must answer seven questions (”expert questions” hereafter) related to statistics and probability calculation. The number of correctly answered questions (”expert score” hereafter) is used as indication of expertise in the second part of the experiment. The second part comprises a typical bookbag-and-pokerchip experiment with the chance to adjust one's own probability estimate after having seen a peer's estimate. The subjects' task is to estimate the likelihood that a ficitional stock is in the good state based on indicative price signals. They are treated based on the information they are given about their peer: Subjects in the control group receive information only about the peer's estimate, while subjects in the treatment group are additionally informed about the peer's expert score ("peer score" hereafter). The variation in the peer score effectively constitutes several treatments within the treatment group, so that we can compare adjustments involving high peer scores to adjustments involving low peer scores. The third part of the experiment is a survey focusing on demographics.

The expert questions focus on statistics and probability calculation, for example the calculation of the expected value of a lottery or the probability of rolling a certain sequence of numbers with a die[7]. We expect that subjects link the skills required to answer these questions to the skills required in the second part of the experiment. All questions are in a multiple-choice format with four answer options out of which one is correct. Subjects must answer every question and cannot return to previous questions. After having answered all seven questions, subjects are informed about the number of questions they answered correctly (while we call this number "expert score" throughout the paper, subjects are never confronted with this term but merely receive the number). As incentive, subjects receive additional £0.20 for each correct answer.

In the bookbag-and-pokerchip experiment subjects are presented with a graphical price development of a fictional stock over five periods[8]. The price development is randomly drawn out of ten previously generated price developments which adhere to the following rules[9]: In period zero the stock price amounts to 100. In every following period the price

[7] See A1 in the Appendix for all seven expert questions.

[8] See A2 in the Appendix for an exemplary stock price development.

[9] The ten price developments are randomly generated according to the underlying price process but selected in such a way, that there are two different price developments for each price increase-decrease-combination, i.e. four price increases and one price decrease. The cases of five price increases respectively decreases constitute exceptions for which there is only one price development each.

either increases by ten or decreases by ten. The likelihood of price increases and decreases depends on the state of the stock, which is either good or bad. In the good state, the likelihood of a price increase (decrease) is 70% (30%) and vice versa for the bad state. Whether the stock is in the good or the bad state is randomly determined in period zero and does not change over the periods. As such, price changes are indicative of the stock's state[10].

To proceed to the actual task, subjects must successfully identify the number of price increases and decreases over the five periods[11]. They are then asked to provide their probability estimate that the stock is in the good state using a slider ranging from 0% to 100%[12]. Theoretically, the correct probability can be determined using Bayesian updating. Afterwards subjects are asked how confident they are that their estimate is within a five percentage point range of the correct probability[13]. They must indicate their confidence on a seven-point scale. On the next page, subjects are told that they were randomly matched with a peer, who, like them, faced the same task a couple of weeks ago, and are provided the peer's estimate. Subjects are also reminded of their own estimate and are then told that they have the chance to adjust their estimate if they want to. In the treatment group, subjects are additionally informed about the peer score and are reminded of their own expert score. Below this information the slider is presented again, using the subjects' initial estimate as default value[14]. Afterwards they are once more asked about their confidence in their estimate.

Subjects were not told that they would be matched with a peer and have the chance to adjust their estimate before starting the experiment. They only become aware of this after facing the peer information after their first initial estimate. The entire bookbag-and-pokerchip task is repeated for up to three independent fictional stocks. The treatment is randomly assigned for each stock, so that one subject can be assigned to the control group for one stock and to the treatment group for another stock. Subjects receive additional £0.50 for each of the final estimates which are within a five percentage point range of the correct probability.

[10] This mechanism is thoroughly explained to the subjects before they are presented with the first price development. See A3 in the Appendix for the instructions.

[11] See A2 in the Appendix

[12] Subjects cannot proceed without at least touching the slider.

[13] The five percentage point range is chosen in line with the incentives for this part of the experiment.

[14] See A4 for the peer information in the control group and A5 for the peer information in the treatment group

Finally, the demographic survey comprises questions regarding the subjects' risk aversion, age and gender.

3 Framework and Hypotheses

We develop the following framework to derive testable hypotheses for our experimental design. There are two individuals, i and j, facing the same probability estimation task. First, i provides an estimate. After having observed j's estimate, i has the chance to adjust their own estimate. From i's perspective the estimate of j can either be confirming (equals i's estimate) or disconfirming (does not equal i's estimate). Intuitively, only disconfirming signal should provide reason to i to adjust their estimate since confirming signals reinforce i in their initial estimate. After having observed j's disconfirming signal i has three options: i can stick to their own estimate, or adjust their initial estimate by either switching to j's estimate or choosing something in between the two estimates[15].

Individual i believes to be right in their estimate with probability 1-$\frac{1}{a_i}x$, where $x \in [0, 1]$ is a general error probability and $a_i > 0$ represents i's confidence in this particular estimate. i's confidence essentially reflects the level of trust i places in their own information processing ability for this estimate. As such, a higher confidence leads to a higher probability of thinking to be right. For $a_i = 1$, i's specific error probability equals the general error probability which i also assumes (without having further information) for any j. A high confidence level can be driven by task-related knowledge and skills but also by overconfidence, resulting in a specific error probability smaller than the general error probability. In addition, i believes that j is right with probability 1-$\frac{1}{b_{i,j}}x$, where x is again the general error probability and $b_{i,j} > 0$ equals i's perceived relative expertise with respect to peer j. Perceived relative expertise captures the information processing ability i assigns their peer j, relative to their own ability. The higher the perceived relative expertise the higher the probability that j is right. In case i has no additional information about j, $b_{i,j}$ takes on a value of 1, such that i's belief that j is right depends only on the general error probability x. The consideration to adjust should solely depend on the confidence level a_i. With additional information about j,

[15] Theoretically, i could also choose something outside the range defined by the two estimates.

$b_{i,j}$ can deviate from 1, such that the specific error probability (1-$\frac{1}{b_{i,j}}x$) depends on $b_{i,j}$[16]. The consideration to adjust does not only depend on i's confidence level a_i, but also on i's perceived relative expertise with respect to j. Everything else equal, we suspect a negative relation between confidence and adjustments and a positive one between perceived relative expertise and adjustments. We thus derive the following two hypotheses:

H1: There is a negative relation between confidence and adjustments.

H2: There is a positive relation between perceived relative expertise and adjustments.

In particular, we hypothesize that higher perceived relative expertise (confidence) leads a) to more (less) adjustments, b) to more (less) subjects switching to their peer estimate instead of sticking to their initial estimate, and b) to adjustments of larger (smaller) magnitude (given that an adjustment is made). Our specified hypotheses are as follows:

H1a: The likelihood of an estimate adjustment decreases when i's confidence level a_i increases.

H1b: The likelihood of switching to the peer estimate compared to sticking to the own estimate decreases when i's confidence level a_i increases.

H1c: The magnitude of the estimate adjustment decreases when i's confidence level a_i increases.

H2a: The likelihood of an estimate adjustment increases when i's perceived relative expertise with respect to j $b_{i,j}$ increases.

H2b: The likelihood of switching to the peer estimate compared to sticking to the own estimate increases when i's perceived relative expertise with respect to j $b_{i,j}$ increases.

H2c: The magnitude of the estimate adjustment increases when i's perceived relative expertise with respect to j $b_{i,j}$ increases.

[16] Given our parameterization it is theoretically possible to calculate negative probabilities of being right. We do not aim to provide a comprehensive model, but merely a framework to think about this problem.

4 Empirical Results

We first describe our data and the variables we construct for the analysis. We then examine our hypotheses by comparing a) adjustments involving high peer scores to adjustments involving low peer scores within the treatment group and b) adjustments in the treatment group to adjustments in the control group. Finally, we test whether information regarding the peer's estimate is beneficial for the subjects.

4.1 Data

The subjects were recruited online using Prolific. We restricted the subject pool to individuals from the UK and the US whose first language is English. To overcome the imbalance between females and males in the Prolific subject pool, we required a balanced sample with respect to gender. It was also ensured that subjects who took part in an earlier experiment could not participate in the current one.

To assemble a database of peers, the experiment was conducted in a modified version in November 2021. Subjects were faced with the task of the bookbag-and-pokerchip experiment five instead of two times and could earn a bonus of £0.40 per estimate within a five percentage point range of the correct probability. Moreover, subjects did not have the chance to readjust their initial estimate since they were not confronted with any peer choice. Overall, 100 subjects participated in the experiment. The median response time was twelve minutes and the subjects earned £3.35 on average.

Based on the subjects' answers the peer database is constructed as follows: For each of the ten price paths all probability estimates are sorted based on the corresponding expert scores. Expert scores from zero to two are sorted into a low score category, expert scores of three and four represent a medium score category and expert scores larger than four form a high score category. Out of each category, several tuples, comprising expert score and probability estimate, are randomly selected in such a way that all three categories are equally represented in the final selection. Probability estimates which indicate the wrong state, i.e.

estimates larger than 50% although the bad state is more likely or estimates smaller than 50% although the good state is more likely, are excluded since such estimates reflect poor understanding of the diagnosticity of the observed price development.

The main experiment was conducted on Prolific twice, first in March 2022 and in August 2022 for replication purposes. In March 2022 150 subjects participated in the experiment. Subjects faced the bookbag-and-pokerchip task two times and assignment to the control group or the treatment group was equally likely. On average the subjects earned £2.60 with a median response time of ten minutes. For the replication experiment in August another 150 subjects were recruited. However, in this experiment the bookbag-and-pokerchip task was conducted three instead of two times and the likelihood of being assigned to the treatment group was two thirds for each task. Subjects earned on average £2.65 while the median working time was eleven minutes. Overall, our sample comprises 750 (150*2+150*3) observations[17] in the bookbag-and-pokerchip task.

Table 1 presents the summary statistics of the subjects' attributes for both experiments separately. Looking at these variables, there seem to be no major differences between the two samples. While the mean age differs significantly (t-stat of 1.97) between the two experiments, the difference is small in magnitude so that we pool the observations of the two experiments to have greater power in our analyses[18].

[Insert Table 1 here]

[17] 450 in the treatment group and 300 in the control group.

[18] For robustness we include - in addition to controlling for age, risk-aversion - wave fixed effects in our analyses to account for unobservable systematic differences between the March and the August experiment and our results remain unchanged.

4.2 Variables

We use subjects' answer to the confidence question after their initial estimate for each price development to capture their confidence level a_i with respect to the specific price development[19]. To internalize perceived relative expertise $b_{i,j}$ in our experiment, we make use of the expert scores of the subjects. We construct our perceived relative expertise measure by subtracting the subject's expert score from the peer score ("score difference" hereafter). In this way, the variable does not only capture the peer's absolute level of expertise, but also the relative aspect of our framework. Score difference is positive (negative) when the peer answered more (less) questions correctly than the subject.

Table 2 displays the pairwise correlation among the explanatory variables. The confidence variable is positively correlated with expert score. Subjects' confidence in the bookbag-and-pokership task is thus, at least partly, derived from their success in answering the expert questions, strengthening our assumption that subjects relate the skills required to answer the expert questions to the skills required for the estimation task. Being male and a lower willingness to take financial risks are also positively correlated with subjects' confidence. We observe worse performance in the expert question task by older subjects, perhaps because knowledge about statistics and probability calculation is gained in younger years and fades out of memory with time. Gender does not seem to be related to the number of correctly answered expert questions. By construction, score difference is highly negatively correlated with expert score and thereby also correlated with confidence and risk-aversion. Regressions reveal that the relation of expert score and score difference crowds out the relation between confidence and score difference.

[Insert Table 2 here]

[19] For robustness, we proxy subjects' confidence in their ability to deal with the bookbag-and-pokerchip task in general by using their answer to the confidence question after the initial estimate of the first price development. At this point subjects do not know that they will be confronted with peer estimates and that they will have the chance to adjust their estimates. This alternative confidence measure is highly correlated ($\rho = 0.79$, $p < 0.01$) with the main one and produces identical results.

4.3 First Glance

Having a first look at the probability estimates reveals that subjects tend to adjust their initial estimate in the direction of their peer's estimate. Figure 1 shows that the higher the difference between the peer's estimate and the own estimate (”estimate difference” hereafter), the higher the adjustment of the initial estimate. However, Figure 1 also reveals that some subjects do not adjust at all although the estimate difference becomes as large as 100 percentage points, effectively indicating the opposite state in the extremest way possible.

[Insert Figure 1 here]

As discussed in the framework and hypotheses section, only disconfirming signals should provide reason to adjust the initial estimate. Table 3 compares the number of adjustments[20] between confirming and disconfirming signals. In line with the prediction, there are no adjustments when subjects are confronted with confirming signals; however, adjustments are frequently made in the case of disconfirming signals. On average, there is almost a 43% chance of adjusting when the signal is disconfirming. Table A1 in the Appendix confirms this finding in a regression setting to account for the dependence of the subjects' decisions and confounding variables.

[Insert Table 3 here]

Taken together, the subjects in our experiments seem to adjust in a meaningful way and only see reason to adjust their initial estimates if they face a disconfirming signal. Since these signals are apparently the most relevant ones for the adjustment decision, we restrict our further analyses to disconfirming signals.

[20] Whenever the final estimate does not equal the subject's initial estimate, we say an adjustment was made.

4.4 Confidence & Expertise

Hypotheses 1 and *Hypothesis 2* predict a positive effect of perceived relative expertise and a negative one of confidence on adjustments. We first examine the adjustment decision (*H1a*, *H1b*, *H2a* and *H2b*) before we turn to the magnitude of the adjustments (*H1c* and *H2c*).

Figure 2 plots the ratio of adjustments for each value of score difference which occurs in the treatment group, i.e. for the different treatments within the treatment group, as well as for each value of confidence that occurs in the treatment group. The ratio of adjustments increases when score difference increases, and decreases when the confidence level increases. Figure 2 thereby illustrates the opposite effects of perceived relative expertise and confidence on the adjustment decision predicted by our hypotheses.

[Insert Figure 2 here]

To test *H1a* and *H2a* formally, we employ a logit regression with an adjustment dummy as dependent variable and score difference and confidence as explanatory variables (Table 4). We effectively examine how higher confidence and a larger score difference compared to lower confidence and a smaller score difference affects the adjustment decision within the treatment group[21]. Specification (1) and (2) test the effect of confidence and expertise separately, while specification (3) to (5) include both perceived relative expertise and confidence so that they can be analysed jointly. Specification (4) and (5) additionally include the control variables and round fixed effects respectively[22]. The coefficient on score difference is positive and significant throughout all specifications. The corresponding marginal effects for specification (5) is 0.03 (0.04 at means). A one point higher peer score relative to the subject's expert score thus increases the likelihood of making an adjustment by 3%, holding self-reported confidence fixed. Confidence on the other hand exhibits a negative and highly significant coefficient in every specification. The marginal effect of specification (5) is -0.04 (-0.05 at means). A

[21] Our sample size thus amounts to 422 observations.

[22] Absolute estimate difference is the only control variable which has a (positive) significant effect on the adjustment decision. It is significant in every specification at the 1% level.

one point higher self-reported confidence level thus decreases the likelihood of making an adjustment by 4%, holding perceived relative expertise fixed. Using linear regressions provides similar results (Table A2).

[Insert Table 4 here]

We construct a new dependent variable to test *H1b* and *H2b*. This alternative adjustment variable equals -1 if the subject sticks to their own initial estimate (final estimate equals the initial estimate) and +1 if the subject switched to their peer's estimate (final estimate equals the peer's estimate). It takes on 0 if the subject's final estimate is any other number. We regress this alternative adjustment variable on confidence, score difference and control variables.

Table 5 shows results which are very similar to our previous findings. Across all specifications, score difference exhibits significant, positive coefficients, while confidence remains negatively significant[23]. Conditional on the self-reported confidence level, a higher score difference increases the likelihood of switching to the peer estimate and decreases the likelihood of sticking to one's own estimate. Vice versa, higher confidence decreases the likelihood of switching to the peer's estimate and increases the likelihood of sticking to one's own estimate, holding perceived expertise fixed. These results also hold when using an ordered logit model instead of linear regressions (Table A3).

Overall, Table 4 and 5 nicely illustrate the opposite effects of perceived relative expertise $b_{i,j}$ and confidence in the specific estimate a_i on the adjustment decision as predicted by *Hypothesis 1* and *Hypothesis 2*.

[Insert Table 5 here]

Turning to the question of the magnitude of the adjustments (*H1c* and *H2c*), we use i) the

[23] Among the control variables, absolute estimate difference also retains its highly significant positive effect. Additionally, being male exhibits a negative effect around the 10% significance level.

absolute adjustment and ii) the ratio of the actual adjustment in percentage points to the estimate difference ("relative adjustment" hereafter) as our magnitude variables. While the relative adjustment variable allows to capture how strongly subjects' follow their peers in relative terms, it is also very sensitive with respect to outliers[24]. Reasonable adjustments should produce relative adjustment values between 0 and 1, so that we restrict our relative magnitude analysis to these cases[25].

We analyse how the magnitude of the adjustment is impacted by expertise and confidence by regressing the magnitude variables on score difference as well as our confidence variables. As Panel A of Table 6 shows, there is a positive significant relation between perceived relative expertise and the absolute magnitude of adjustments for all specifications. There is a sharp increase in the R^2 once the control variables are introduced. This is due to absolute estimate difference, which exhibits a highly significant coefficient of around 0.70 in all specifications[26]. Controlling for absolute estimate difference, the effect of perceived relative expertise becomes even stronger in terms of magnitude as well as significance. In particular, the absolute adjustment increases by 1.56 percentage points when score difference increases by one point (Specification (5)). Given that the median (mean) absolute estimate difference is 18 (22) percentage points, this is a sizable effect. Confidence, however, does not significantly relate to the magnitude of the adjustment. Panel B presents our results for the relative adjustment variable, confirming our results from the absolute adjustment analysis. The coefficients on perceived relative expertise are positive and highly significant throughout all specifications, whereas confidence has no significant effect[27]. A one point higher score difference leads to an increase in the relative adjustment of 0.05, which is economically meaningful since the median (mean) relative adjustment equals 0.50 (0.56). The evidence suggests that once a subject has decided to make an adjustment, it only relies on perceived relative expertise but not confidence to determine the magnitude of their adjustment.

[24] For example, one subject adjusted their estimate from 50% to 58% after having observed a peer estimate of 51%, resulting in a relative adjustment value of 8.

[25] Out of 186 decisions, we remove 14 decisions with relative adjustment values smaller than zero respectively larger than one, so that the final sample comprises 158 decisions.

[26] No other control variable has a significant effect.

[27] Among the control variables absolute estimate difference retains a positive significant effect at the 5% level and being male has a negative effect at the 10% level.

[Insert Table 6 here]

We rerun our previous analyses using peer score and expert score as expertise measures instead of score difference. Table 7 presents the estimates of regressions equivalent to specification (5) of Table 4 to Table 7 but using these alternative expertise measures. Both alternative expertise measures have a significant effect in the expected direction in all regressions. The higher the expertise of the peer, the higher the likelihood of an adjustment and the larger the magnitude of an adjustment. An increase in the subject's expertise decreases the likelihood of an adjustment as well as the magnitude of an adjustment. Moreover, the magnitude of the estimates is (except for the absolute adjustment) similar in absolute terms between the two variables, suggesting that both expertise variables have a comparable effect. As before, confidence has a highly significant, negative effect on the adjustment decision, but no significant effect on the magnitude of the adjustments. Neither peer score nor expert score, however, provide estimates, which are consistently as significant in all regressions as the ones for score difference, thereby strengthening our assumption that the relative aspect of expertise is of particular importance.

[Insert Table 7 here]

Taken together, the evidence strongly supports *Hypothesis 1* and *Hypothesis 2*, implying that perceived relative expertise and confidence in the estimate positively respectively negatively relate to adjustments. While perceived relative expertise matters for the adjustment decision as well as the magnitude of the adjustments, confidence seems to have an effect on the adjustment decision but not on the magnitude of the adjustments.

4.5 Non-Linearity

We conduct median splits to examine potential non-linearities in the effects of confidence and perceived relative expertise on the adjustment decision[28]. The median (mean) of confidence and score difference is 3 (3.43) respectively 1 (0.64). We compare higher than median with lower than or equal to median values to divide the sample almost evenly[29].

Table 8 shows the median split for confidence, using regressions equivalent to specification (5) of our previous analyses. For high confidence levels, the effect of score difference is reduced in magnitude and significance. Vice versa, the effect of confidence vanishes for low confidence levels. For subjects who do not have much confidence, the precise confidence level is not relevant but score difference is. Subjects who are confident in their judgement, however, place less weight on score difference, leaving the precise confidence level with a strong effect.

[Insert Table 8 here]

In Table 9 we present the median split for score difference. We find that score difference is of less importance for high score difference levels, exhibiting smaller coefficients of reduced significance. Confidence on the other hand matters only for high score difference values, but not for low ones. For subjects who observe a peer with lower or equal expertise, score difference clearly matters but the confidence level does not. Subjects place less weight on score difference when observing a peer with higher expertise, but confidence has a highly significant effect.

[Insert Table 9 here]

Whenever one of the two variables implies a lower likelihood of adjusting (high confidence or low score difference as opposed to low confidence or high score difference), this variable

[28] We we refrain from extending our non-linearity analysis to the magnitude of adjustments due to the much smaller sample size.

[29] For confidence, 53% of observations are above the median, for score difference 46%.

exhibits a stronger effect at the expense of the other variables, which has a weaker effect. Each variable has a stronger effect when it does not suggest an adjustment itself, and a stronger effect when the other variable suggests an adjustment. The effect of score difference is thus the strongest when the effect of confidence is the weakest. This is the case when a subject has low confidence and observes a peer with lower or equal expertise. Similarly, the effect of confidence is the strongest when the one of score difference is the weakest, which is the case when a subject has high confidence and observes a peer with higher expertise. Table A4 in the Appendix, which reports the coefficients for joint median splits on confidence and score difference, confirms this[30].

Overall, these findings suggest non-linear effects of confidence and perceived relative expertise. Subjects pay more attention to their peer's relative expertise (instead of confidence) when they do not trust their own information processing ability but do not have a peer they can easily rely on. Subjects pay more attention to their confidence in their own information processing ability (instead of their peer's relative expertise) when they trust their own information processing ability but are confronted with a (more) capable peer.

4.6 Treatment vs. Control

So far, we have analysed how higher perceived relative expertise influences adjustments compared to lower perceived relative expertise within the treatment group. We now focus on perceived relative expertise's impact relative to having no information about the peer's expertise. In Panel A of Table 10 the ratio of adjustments between the control and treatment group are compared. The ratio of adjustments is slightly higher in the treatment group, but this difference is not significant so that the treatment by itself appears to have no major effect on the adjustment decision. Panel B displays the ratio of adjustments for each value of score difference which occurs in the treatment group[31]. While the ratio of adjustments is not growing linearly, it is clearly increasing with score difference. Compared to the control group, the ratio of adjustments is lower for score differences smaller than -1 and higher for

[30] The positive coefficient on confidence in the bottom right in both Panels is due to the fact that adjustments increase with confidence for this particular sub-sample, but can also be interpreted as weakest effect since it is opposing the usual direction of the effect.

[31] These values are illustrated in Figure 2.

score differences larger than 1. It appears that being provided with information regarding the peer's expertise matters for the adjustment decision only if the peer's expertise sufficiently deviates from the subject's expertise.

We therefore construct a higher and a lower peer score dummy variable which equals 1 if score difference is larger than 1 respectively smaller than -1 and which equals 0 if the subject has not received information regarding the peer score.

[Insert Table 10 here]

To examine the influence of the peer's expertise information compared to the control group, we regress the adjustment dummy on the newly created higher (lower) peer score dummy using a logit model (*H2a*). Table 11 displays positive and significant coefficients for the higher peer score dummy in all specifications. The coefficients on the lower peer score dummy are negative but just not significant in most specifications[32]. Using specification (4), we estimate a marginal effect of 0.09 (0.10 at means) for the higher peer score dummy. A one point higher score difference compared to not observing a peer score increases the likelihood of adjusting by 9%. As before, confidence has a significant negative effect on adjustments. Table A5 in the Appendix confirms our findings using linear regressions.

[Insert Table 11 here]

We also regress the alternative adjustment variable on the peer score dummies to verify *H2b* (Table 12). The estimated coefficients are all in the expected direction and significant, indicating that a higher (lower) score difference, compared to observing no information regarding the peer's expertise, increases (decreases) the likelihood of switching to the peer decision and decreases (increases) the likelihood of sticking to one's own decision. Confidence

[32] The corresponding p-value is around 0.15.

retains its negative effect on adjustments. The results remain unchanged when using an ordered logit regression (Table A6).

[Insert Table 12 here]

To test *H2c* in this setting, we examine the magnitude of the adjustment by regressing the adjustment variables on the higher respectively lower peer score dummy variables (Table 13). For both absolute and relative adjustments, we estimate coefficients which are in line with the hypothesis and highly significant in all specifications once we control for the absolute estimate difference. Observing a peer with higher (lower) expertise compared to no expertise information leads to larger (smaller) adjustments in absolute and relative terms. Interestingly, confidence has a highly significant, negative effect on relative adjustments. Further regressions, which analyse the control group and the subjects who observe an absolute score difference larger than 1 separately, indicate that this effect is driven by the control group. In the absence of information regarding the peer's expertise subjects seem to rely on their confidence to determine the relative magnitude of their adjustment.

[Insert Table 13 here]

Taken together, the evidence in the treatment vs. control scenario further supports *Hypothesis 2*.

4.7 Impact of the Adjustments

Finally, we examine whether subjects are better off when looking for a more capable peer.

In Table 14 it can be seen that the subjects' confidence in their estimate increases by observing their peer's estimate. Given that the signal is disconfirming (Panel A) this effect is more than twice as strong for those who adjust compared to those who do not adjust (0.40

vs. 0.14). This effect is mainly driven by the fact that, in line with our previous results, the confidence level before the adjustment opportunity of those who adjust is more than half a point lower than the one of those who do not adjust. This gap in confidence remains after the adjustment, but reduces significantly to 0.28 due to the stronger increase in confidence for those who adjust. The increase in confidence is strongest when observing a confirming signal (Panel B), which validates the own initial estimate. The evidence suggests that the subjects' confidence - as measure of trust in their estimate - increases either due to observing a confirming signal which does not trigger an adjustment or by adjusting in line with the decision of a supposedly more capable peer.

[Insert Table 14 here]

To see whether adjusting the initial estimate after observing the peer's estimate increases the subjects' performance in the bookbag-and-pokerchip task, we look at the ratio of correct estimates (i.e., the estimates which are in a five percentage point range of the correct probability). Since we constructed the peer database in such a way that peers with high expert scores occur more often than in a random sample, we expect the peers to exhibit a higher ratio of correct estimates. Indeed, 34% of peer estimates are correct whereas only 29% of the subjects' initial estimates are correct; this difference is also statistically significant (t-stat of 1.98)[33].

Table 15 shows that for those who adjust the ratio of correct estimates is significantly larger after the adjustment compared to before. Adjusting increases the subjects' likelihood of providing a correct estimate by more than one third (0.34 vs. 0.25). As for confidence, those who adjust seem to do worse to start with; before observing the peer information the ratio of correct estimates of those who adjust is six percentage points lower than the ratio of those who do not adjust. This difference is just not significant at the 10% level. After the adjustment opportunity the ratio of those who adjust is slightly but not significantly larger

[33] In line with previous analyses we restrict the sample to disconfirming signals.

than the ratio of those who do not adjust. Adjusting the initial estimate based on the peer's estimate thus improves the subjects' performance.

[Insert Table 15 here]

Overall, adjusting is beneficial to the subjects who adjust. It not only increases subjects' confidence in their estimate, but also leads to significantly more correct estimates.

5 Conclusion

We provide experimental evidence that information processing is a relevant channel through which peer effects occur: Individuals value peers who are more capable in processing common information than themselves. As such, peer effects persist even in situations in which peers do not possess additional information.

We find a negative effect of confidence in an estimate, reflecting trust in one's own information processing ability, on peer effects; and a positive effect of relative perceived peer expertise, capturing the perception of the peer's information processing ability relative to one's own. Individuals' confidence reduces peer effects. Subjects in our experiment adjust their probability estimate after observing their peer's estimate less frequently with increasing confidence. Perceived relative expertise on the other hand increases peer effects. We find that the number of adjustments as well as the magnitude of the adjustments increases with increasing perceived relative expertise of the peer. Having the opportunity to take the peer's estimate into account improves the subjects performance: Adjusting one's own initial estimate after observing the peer's estimate increases the likelihood of providing a correct estimate by one third.

We thereby add the information processing channel to the peer effects literature. We think of it as another mechanism within the social learning strand of the literature. Although individuals do not receive additional information, their social network nevertheless provides them with information. Specifically, it allows the individuals to infer from their peers' decisions how common information should be processed. Moreover, we provide evidence that peers' expertise is an important trait which has a positive impact on peer effects and negatively scales the effect of commitment.

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Figure 1: Overall Adjustments

This figure plots all adjustments (adjusted estimated minus initial estimate) against the estimate difference (peer estimate minus intial estimate).

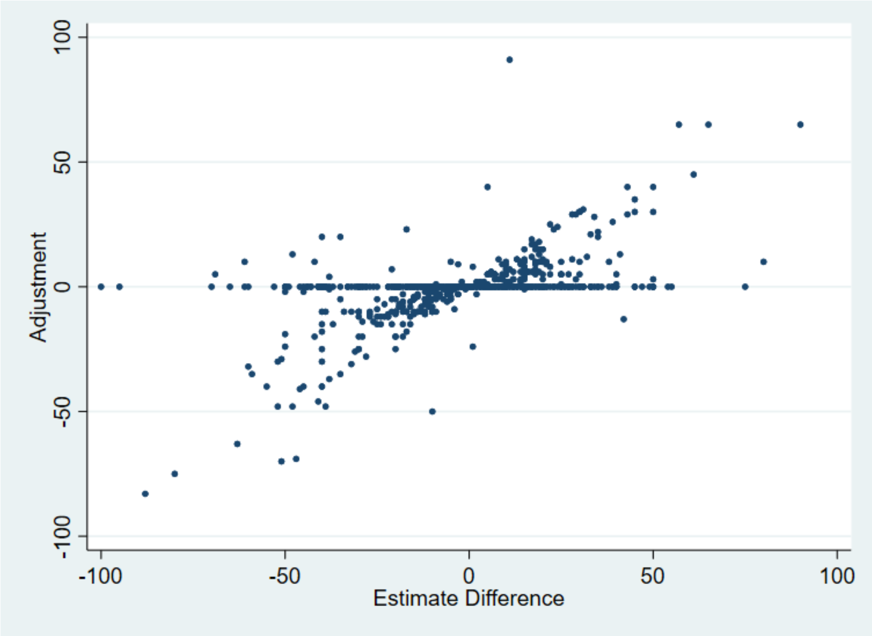


Figure 2: Mean Adjustment

This figure plots the ratio of adjustments for each score difference respectively confidence value which occurs in the treatment group. The sample is restricted to disconfirming signals.

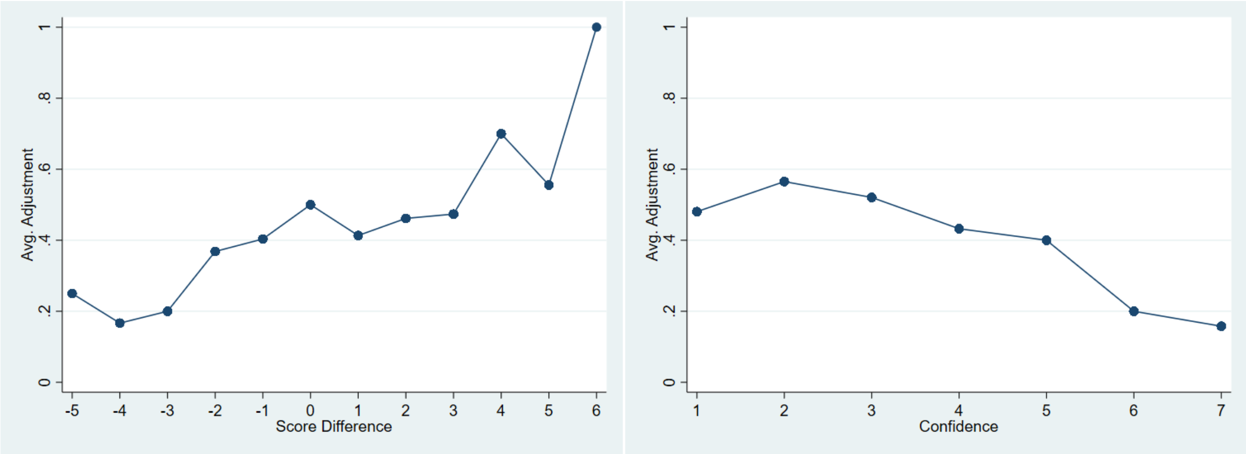


Table 1: Summmary Statistics

This table shows summary statistics for the March respectively August experiment.

	Mean	Median	Min	Max	SD
March					
age (N=150)	40.17	37.50	18.00	75.00	13.82
risk-aversion (N=150)	4.55	4.00	1.00	7.00	1.62
gender (male) (N=150)	0.49	0.00	0.00	1.00	0.5
expert score (N=150)	2.66	3.00	0.00	6.00	1.26
confidence (N=300)	3.31	3.00	1.00	7.00	1.73
August					
age (N=150)	37.10	35.00	19.00	71.00	13.17
risk-aversion (N=150)	4.69	5.00	1.00	7.00	1.62
gender (male) (N=150)	0.49	0.00	0.00	1.00	0.50
expert score (N=150)	2.85	3.00	0.00	7.00	1.35
confidence (N=450)	3.46	3.00	1.00	7.00	1.75

Table 2: Pairwise Correlation

This table shows the pairwise correlation among the explanatory variables. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	confidence	*score difference*	*expert score*	*male*	*age*
score difference	-0.14***				
expert score	0.20***	-0.64***			
male	0.26***	-0.08*	0.06		
age	-0.02	0.12**	-0.21***	0.05	
risk aversion	-0.19***	0.15***	-0.13***	-0.25***	0.13***

Table 3: Disconfirming Signal - t-test

This table shows a t-test to compare the ratio of adjustments between confirming and disconfirming signals. Disconfirming signal are defined as peer estimates which do not equal one's own estimate.

	confirming signal	disconfirming signal	difference
no adjustment	47	402	
adjustment	0	301	
in %	0.00	42.82	-42.82
			-5.92 *(*t-stat)

Table 4: Adjustment Decision 1: Logit Regression

This table shows logit regressions with an adjustment dummy as dependent variable and score difference and confidence (and control variables) as explanatory variables. The sample is restricted to disconfirming signals. Standard errors are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)
score difference	0.15***		0.13***	0.14***	0.14***
confidence		-0.22***	-0.20***	-0.21***	-0.20***
controls	No	No	No	Yes	Yes
round FE	No	No	No	No	No
N	422	422	422	422	422
Pseudo-R^2	0.02	0.03	0.04	0.07	0.08

Table 5: Adjustment Decision 2: Linear Regression

This table shows linear regressions with an adjustment variable which equals -1 if one sticks to one's own estimate and +1 if one switches to the peer estimate as dependent variable and score difference and confidence (and control variables) as explanatory variables. The sample is restricted to disconfirming signals. Standard errors are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)
score difference	0.05***		0.04***	0.04***	0.04***
confidence		-0.07***	-0.06***	-0.06***	-0.06***
controls	No	No	No	Yes	Yes
round FE	No	No	No	No	Yes
N	422	422	422	422	422
R^2	0.03	0.04	0.07	0.09	0.11

Table 6: Adjustment Magnitude

This table shows linear regressions with the adjustment variables as dependent variables and score difference and confidence (and control variables) as explanatory variables. Panel A uses the absolute adjustment magnitude variable and Panel B the relative adjustment magnitude variable. The sample is restricted to disconfirming signals. Standard errors are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Panel A: Absolute Adjustment					
	(1)	(2)	(3)	(4)	(5)
score difference	1.33**		1.33**	1.50***	1.56***
confidence		-0.20	0.04	-0.60	-0.40
controls	No	No	No	Yes	Yes
round FE	No	No	No	No	Yes
N	186	186	186	186	186
R^2	0.03	0.00	0.03	0.54	0.55
Panel B: Relative Adjustment					
	(1)	(2)	(3)	(4)	(5)
expertise	0.05***		0.05***	0.04***	0.04***
confidence		-0.02	-0.02	-0.01	-0.01
controls	No	No	No	Yes	Yes
round FE	No	No	No	No	Yes
N	158	158	158	158	186
R^2	0.11	0.02	0.12	0.18	0.21

Table 7: Alternative Expertise Measures

This table shows regressions equivalent to specification (5) of Table 4 to Table 7 using alternative expertise measures instead of score difference. Panel A uses peer score and Panel B expert score. The sample is restricted to disconfirming signals. Standard errors are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Panel A: Peer Score	Adjustment Decision 1	Adjustment Decision 2	Absolute Adjustment	Relative Adjustment
peer score	0.13*	0.05***	0.99*	0.03*
confidence	-0.22***	-0.06***	-0.50	-0.01
controls	Yes	Yes	Yes	Yes
round FE	Yes	Yes	Yes	Yes
N	422	422	186	158
(Pseudo-)R^2	0.07	0.10	0.52	0.17
Panel B: Expert Score	Adjustment Decision 1	Adjustment Decision 2	Absolute Adjustment	Relative Adjustment
expert score	-0.16*	-0.04*	-2.33***	-0.05***
confidence	-0.19***	-0.06***	-0.38	-0.01
controls	Yes	Yes	Yes	Yes
round FE	Yes	Yes	Yes	Yes
N	422	422	186	158
(Pseudo-)R^2	0.07	0.09	0.54	0.19

Table 8: Median Split: Confidence

This table shows median splits for confidence. Panel A uses an adjustment dummy and Panel B an adjustment variable which equals -1 if one sticks to one's own estimate and +1 if one switches to the peer estimate as dependent variable. Score difference, confidence (and control variables) are explanatory variables. The sample is restricted to disconfirming signals. Standard errors are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Panel A: Adjustment Decision 1		
	$\leq$ *median*	$>$ *median*
score difference	0.16**	0.10
confidence	0.26	-0.50***
controls	Yes	Yes
round FE	Yes	Yes
N	219	203
Pseudo-R^2	0.08	0.09
Panel B: Adjustment Decision 2		
	$\leq$ *median*	$>$ *median*
score difference	0.05**	0.03**
confidence	0.03	-0.11***
controls	Yes	Yes
round FE	Yes	Yes
N	219	203
R^2	0.08	0.12

Table 9: Median Split: Score Difference

This table shows median splits for score difference. Panel A uses an adjustment dummy and Panel B an adjustment variable which equals -1 if one sticks to one's own estimate and +1 if one switches to the peer estimate as dependent variable. Score difference, confidence (and control variables) are explanatory variables. The sample is restricted to disconfirming signals. Standard errors are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Panel A: Adjustment Decision 1		
	$\leq$ *median*	$>$ *median*
score difference	0.35**	0.22*
confidence	-0.08	-0.23***
controls	Yes	Yes
round FE	Yes	Yes
N	195	227
Pseudo-R^2	0.14	0.07
Panel B: Adjustment Decision 2		
	$\leq$ *median*	$>$ *median*
score difference	0.08***	0.07*
confidence	-0.02	-0.08***
controls	Yes	Yes
round FE	Yes	Yes
N	195	227
R^2	0.14	0.11

Table 10: Ratio of Adjustments

Panel A of this table shows t-tests to compare the ratio of adjustments between treatment and control group. Panel B displays the ratio of adjustments for each score difference value which occurs in the treatment group. The sample is restricted to disconfirming signals.

Panel A: Control vs. Treatment	control	treatment	difference
no adjustment	166	236	
adjustment	115	186	
in %	40.93	44.08	-3.15
			-0.83 (t-stat)

Panel B: Score Difference score difference	-5	-4	-3	-2	-1	0	1	2	3	4	5	6
no adjustment	3	5	16	24	34	35	44	35	30	6	4	0
adjustment	1	1	4	14	23	35	31	30	27	14	5	1
in %	25.00	16.67	20.00	36.84	40.35	50.00	41.33	46.15	47.37	70.00	55.56	100.00

Table 11: Adjustment Decision 1: Higher and Lower Score Difference - Logit Regression

This table shows logit regressions with an adjustment dummy as dependent variable and the higher respectively lower peer score dummy and confidence (and control variables) as explanatory variables. The sample is restricted to disconfirming signals. Standard errors are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
higher peer score	0.39*	0.40*	0.40*	0.40*				
lower peer score					-0.51*	-0.39	-0.42	-0.44
confidence		-0.19***	-0.18***	-0.17***		-0.17**	-0.16**	-0.14**
controls	No	No	Yes	Yes	No	No	Yes	Yes
round FE	No	No	No	Yes	No	No	No	Yes
N	433	433	433	433	349	349	349	349
Pseudo-R^2	0.01	0.02	0.04	0.05	0.01	0.02	0.06	0.08

Table 12: Adjustment Decision 2: Higher and Lower Score Difference - Linear Regression

This table shows linear regressions with an adjustment variable which equals -1 if one sticks to one's own estimate and +1 if one switches to the peer estimate as dependent variable and the higher respectively lower peer score dummy and confidence (and control variables) as explanatory variables. The sample is restricted to disconfirming signals. Standard errors are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
higher peer score	0.11*	0.11*	0.11*	0.12*				
lower peer score					-0.16**	-0.12*	-0.12*	-0.12*
confidence		-0.07***	-0.06***	-0.06***		-0.06***	-0.05***	-0.04**
controls	No	No	Yes	Yes	No	No	Yes	Yes
round FE	No	No	No	Yes	No	No	No	Yes
N	433	433	433	433	349	349	349	349
R^2	0.01	0.04	0.08	0.09	0.01	0.04	0.10	0.11

Table 13: Adjustment Magnitude: Higher and Lower Score Difference - Linear Regression

This table shows linear regressions with the magnitude of adjustment as dependent variable and the higher respectively lower peer score dummy and confidence (and control variables) as explanatory variables. Panel A uses the absolute adjustment variable and Panel B the relative adjustment variable. The sample is restricted to disconfirming signals. Standard errors are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Panel A: Absolute Adjustment								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
higher peer score	3.51	3.44	4.01**	3.98**				
lower peer score					-4.66***	-4.43***	-4.70***	-4.44**
confidence		-0.29	-0.60	-0.60		-0.63	-0.58	-0.56
controls	No	No	Yes	Yes	No	No	Yes	Yes
round FE	No	No	No	Yes	No	No	No	Yes
N	192	192	192	192	135	135	135	135
R^2	0.02	0.02	0.33	0.33	0.02	0.03	0.31	0.33
Panel B: Relative Adjustment								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
higher peer score	0.06	0.06	0.07*	0.07*				
lower peer score					-0.18**	-0.15**	-0.17**	-0.17**
confidence		-0.03**	-0.03**	-0.03**		-0.04**	-0.04***	-0.04**
controls	No	No	Yes	Yes	No	No	Yes	Yes
round FE	No	No	No	Yes	No	No	No	Yes
N	174	174	174	174	124	124	124	124
R^2	0.01	0.05	0.11	0.15	0.05	0.09	0.20	0.24

Table 14: Impact: Confidence

This table shows the coefficients of linear regressions to compare the subjects' confidence level before and after the adjustment opportunity for those who adjust and those who do not adjust. Panel A restricts the sample to disconfirming signals, Panel B restricts the sample to confirming signals. Standard errors are clustered at the individual level. ***, ** and * are used to denote significance at the 1%, 5% and 10% level (two-sided) respectively.

Panel A: Disconfirming Signals	before	after	difference
no adjustment (N=402)	3.61	3.76	-0.14***
adjustment (N=301)	3.07	3.47	-0.40***
difference	0.54***	0.28**	0.26***
Panel B: Confirming Signals	before	after	difference
no adjustment (N=47)	3.66	4.32	-0.66***

Table 15: Impact: Correct Estimates

This table shows the coefficients of linear regressions to compare the ratio of correct estimates (estimates within 5 percentage points of the correct probability) before and after the adjustment opportunity for those who adjust and those who do not adjust. The sample is restricted to disconfirming signals. Standard errors are clustered at the individual level. ***, ** and * are used to denote significance at the 1%, 5% and 10% level (two-sided) respectively.

	before	after	difference
no adjustment (N=402)	0.31	0.31	0.00
adjustment (N=301)	0.25	0.34	-0.08**
difference	0.06	-0.02	0.08**

A Additional Tables and Figures

Figure A1: Expert Questions

Section 1 - Question 1

What does the term "correlation" refer to in statistics?

- ○ The relation between two variables.
- ○ The causal influence of one variable on another variable.
- ○ The ratio of expected value to dispersion of one variable.
- ○ The dispersion of one variable.

Section 1 - Question 2

What is the expected value of a lottery which pays
-3 with 25% probability,
0 with 25% probability,
3 with 50% probability?

- ○ 0
- ○ 0.25
- ○ 0.75
- ○ 1

Section 1 - Question 3

What is the probability of throwing exactly two "6" when rolling a fair die three times (the order does not matter)?

- ○ 1/216
- ○ 5/216
- ○ 15/216
- ○ 27/216

Section 1 - Question 4

What is the variance of a variable which has the following population values: 2, 4 and 6?

- ○ 2
- ○ 8/3
- ○ 4
- ○ 16/3

Section 1 - Question 5

An urn contains 10 balls: 3 red ones and 7 black ones. What is the probability of drawing a red ball first and a black ball second (once a ball is drawn, it is not returned to the urn)?

- ○ 1/21
- ○ 9/21
- ○ 21/100
- ○ 21/90

Section 1 - Question 6

What is the median of the following sample: 3, 3, 5, 7 and 12?

- ○ 3
- ○ 5
- ○ 6
- ○ 12

Section 1 - Question 7

Estimate the probability that in a group of 10 people at least 2 people have their birthday in the same week (assume that births are equally distributed among all weeks of the year)?

- ○ Approximately 30%
- ○ Approximately 40%
- ○ Approximately 50%
- ○ Approximately 60%

Figure A2: Exemplary Stock Price Development

Section 2 - Stock price development 1

You now see the price development of the first fictional stock over 5 periods.

A period is defined as every movement from one point in time to the next. Thus, moving from time 0 to time 1 is the first period, moving from time 1 to time 2 is the second period and so on.

How many price increases and decreases did the stock experience over the 5 periods?

- ○ 0 increases and 5 decreases
- ○ 1 increase and 4 decreases
- ○ 2 increases and 3 decreases
- ○ 3 increases and 2 decreases
- ○ 4 increases and 1 decrease
- ○ 5 increases and 0 decreases

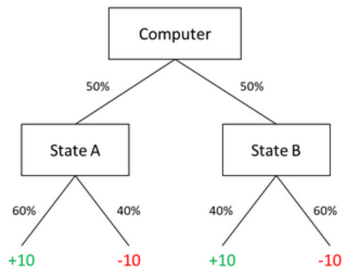
Figure A3: Instructions

Section 2 - Instructions

Compensation
In this section, you will have to estimate probabilities. Your compensation increases by £0.50 if your estimate is within 5% of the correct probability (e.g. the correct probability is 50% and your estimate is between 45% and 55%).

Task Description
You will see the price development of a fictional stock over 5 periods. There are 2 states of the world, state A and state B, of which one was randomly selected by the computer. The selected state of the world determines the price development of the fictional stock for all periods.

Every period the stock price can either increase or decrease by 10 units. If state A (the "good" state) was selected, the probability of an increase (60%) is higher than the probability of a decrease (40%). If state B (the "bad" state) was selected, the probabilities are reversed, i.e. the probability of a decrease (60%) is higher than the probability of an increase (40%).
As such, price increases and decreases are indicative of which state of the world was selected.



Based on the observable stock price development, you will have to estimate the probability that state A (the "good" state) was selected by the computer.

This task will be repeated for a second and a third stock. The state of the world is determined separately for each stock, i.e. the first stock's price development is not indicative of the state of the world underlying the second or third stock's price development and vice versa. At the time of the estimates the above explanation will be presented again.

Press "Next" to begin the task.

Figure A4: Exemplary Peer Information Control Group

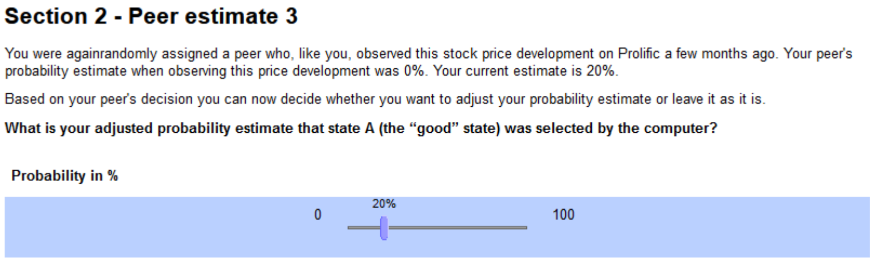
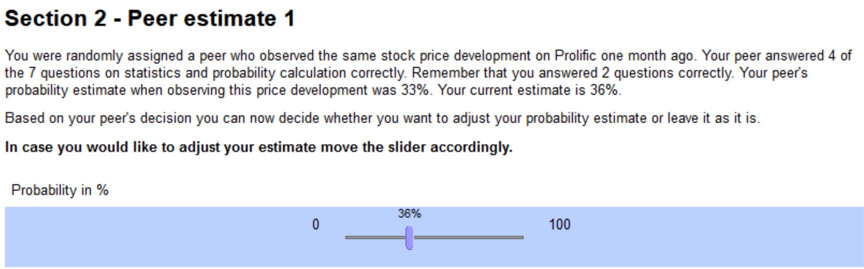


Figure A5: Exemplary Peer Information Treatment Group



Section 2 - Peer estimate 1

You were randomly assigned a peer who observed the same stock price development on Prolific one month ago. Your peer answered 4 of the 7 questions on statistics and probability calculation correctly. Remember that you answered 2 questions correctly. Your peer's probability estimate when observing this price development was 33%. Your current estimate is 36%.

Based on your peer's decision you can now decide whether you want to adjust your probability estimate or leave it as it is.

In case you would like to adjust your estimate move the slider accordingly.

Probability in %

Table A1: Disconfirming Signal - Linear Regression

This table shows linear regressions with an adjustment dummy as dependent variable and the disconfirming signal indicator (and control variables) as explanatory variable. Disconfirming signal are defined as peer estimates which do not equal one's own estimate. Standard errors are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)
disconfirming signal	0.43***	0.33***	0.35***
controls	No	Yes	Yes
round FE	No	No	Yes
N	750	750	750
R^2	0.05	0.10	0.11

Table A2: Adjustment Decision 1: Linear Regression

This table shows linear regressions with an adjustment dummy as dependent variable and score difference and confidence (and control variables) as explanatory variables. The sample is restricted to disconfirming signals. Standard errors are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)
score difference	0.04***		0.03***	0.03***	0.03***
confidence		-0.05***	-0.05***	-0.05***	-0.04***
controls	No	No	No	Yes	Yes
round FE	No	No	No	No	No
N	422	422	422	422	422
R^2	0.02	0.03	0.05	0.09	0.10

Table A3: Adjustment Decision 2: Ordered Logit

This table shows ordered logit regressions with an adjustment variable which equals -1 if one sticks to one's own estimate and +1 if one switches to the peer estimate as dependent variable and score difference and confidence (and control variables) as explanatory variable. The sample is restricted to disconfirming signals. Standard errors are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)
score difference	0.17***		0.15***	0.16***	0.17***
confidence		-0.24***	-0.22***	-0.22***	-0.21***
controls	No	No	No	Yes	Yes
round FE	No	No	No	No	Yes
N	422	422	422	422	422
R^2	0.02	0.03	0.04	0.06	0.07

Table A4: Median Split: Confidence & Score Difference

This table shows the coefficients for median splits for confidence and score difference combined. The first number gives the coefficient on score difference, the second the coefficient on confidence. Panel A uses an adjustment dummy and Panel B an adjustment variable which equals -1 if one sticks to one's own estimate and +1 if one switches to the peer estimate as dependent variable. Score difference, confidence (and control variables) are explanatory variables. All regressions include fixed effects. The sample is restricted to disconfirming signals. Standard errors are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Panel A: Adjustment Decision 1		
	confidence $\leq$ *median*	confidence $>$ *median*
score difference $\leq$ *median*	0.42** / 1.09***	0.34 / -0.51*
score difference $>$ *median*	0.25 / -0.10	0.17 / -0.51**
Panel B: Adjustment Decision 2		
	confidence $\leq$ *median*	confidence $>$ *median*
score difference $\leq$ *median*	0.10* / 0.22***	0.06* / -0.09*
score difference $>$ *median*	0.07 / -0.08	0.05 / -0.13**

Table A5: Adjustment Decision 1: Higher and Lower Score Difference - Linear Regression

This table shows linear regressions with an adjustment dummy as dependent variable and the higher respectively lower peer score dummy and specific confidence (and control variables) as explanatory variables. The sample is restricted to disconfirming signals. Standard errors are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
higher peer score	0.10*	0.10*	0.09*	0.09*				
lower peer score					-0.11*	-0.09	-0.09	-0.09
confidence		-0.05***	-0.04***	-0.04***		-0.04**	-0.04**	-0.03**
controls	No	No	Yes	Yes	No	No	Yes	Yes
round FE	No	No	No	Yes	No	No	No	Yes
N	433	433	433	433	349	349	349	349
R^2	0.01	0.03	0.06	0.07	0.01	0.03	0.08	0.10

Table A6: Adjustment Decision 2: Higher and Lower Score Difference - Ordered Logit

This table shows ordered logit regressions with an adjustment variable which equals -1 if one sticks to one's own estimate and +1 if one switches to the peer estimate as dependent variable and the higher respectively lower peer score dummy and confidence (and control variables) as explanatory variables. The sample is restricted to disconfirming signals. Standard errors are clustered at the individual level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
higher peer score	0.39**	0.39**	0.39*	0.41*				
lower peer score					-0.54*	-0.42	0.48*	-0.49*
confidence		-0.22***	-0.21***	-0.19***		-0.19***	-0.18**	-0.16*
controls	No	No	Yes	Yes	No	No	Yes	Yes
round FE	No	No	No	Yes	No	No	No	Yes
N	433	433	433	433	349	349	349	349
Pseudo-R^2	0.01	0.02	0.04	0.05	0.01	0.02	0.06	0.07