An Experimental Assessment of Learning Ability, Responsiveness to Advice and Peer Effects in Adoption Choices

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Abstract

This article explores the linkages between learning ability, responsiveness to advice and peer effects and examines their role in adoption choices. A laboratory experimental method is used. The experimental games consist of cue-learning tasks in which participants play multiple rounds and receive feedback (or advice) of how various cues translate into different outcomes. Preliminary results suggest that participants make better choices when receiving formal advice compared to when receiving advice from peers. The final results will likely provide recommendations for optimal information provision for farmers to foster the uptake of new technologies.

Keywords: laboratory experiments, behavioural economics, learning, advice taking, technology adoption.

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1. Introduction

Sustainable intensification is becoming increasingly important, which mainly stems from the recognition that the current growth path in agricultural production will lead to using natural resources beyond their capacity (OECD, 2013). A growing population, increasing awareness of the impact of climate change on food production as well as an increasing realisation that intensive agriculture has detrimental effects on the environment has added to the understanding of the importance of sustainable food production (OECD, 2014; DAFM, 2011). The adoption of new technologies and production methods by farmers can significantly contribute to the achievement of a more sustainable and productive agricultural sector (OECD, 2015).

In order to adopt new technologies and innovations, learning and advice are important as innovations are often imperfectly known and farmers require information before deciding whether or not to adopt. However, the process by which farmers learn and utilise information about innovations is poorly understood. Despite an extensive literature focusing on technology uptake in agriculture, few studies directly examine learning and information use of farmers. Farmers generally learn from a number of sources, for example from extension services, learning by doing or their peers. However, in the literature various learning and information sources have rarely been taken into account simultaneously. Most studies attempt to infer learning via how adoption diffuses across farmers who might be geographically or spatially proximate (see Rogers, 2010).

Moreover, farmers are often slow to adopt new technologies. For example, there is a lack of adoption of efficient grassland practices (DAFM, 2011), a low engagement with computers (Hennessy et al., 2016) or uptake of optimal herd management techniques (Dillon et al., 2015) among Irish farmers. In addition, many of the available new technologies are low-cost (in terms of capital expenditure), but are high-cost in terms of information acquisition, which further underlines the importance of learning in adoption choices.

In this article, we make a unique contribution to the existing literature by considering several learning and information sources. Specifically, we explore the linkages between learning ability, responsiveness to advice and peer effects and examine their role in adoption choices. Our methodology overcomes the empirical difficulty in directly relating learning by doing, advice and social learning to farmers' adoption choices using field data. To this end, we employ laboratory experiments that measure learning ability and responsiveness to formal advice as well as peers; then we link these measures to adoption choices. Hence, this study aims to help overcome low adoption rates by farmers of new technologies by focusing on learning in technology choices and providing solutions for optimal information provision to farmers to better foster uptake of new technologies.

2. Literature Review

Learning and information provision are pivotal in adoption decisions where innovations are imperfectly known and farmers require information before deciding whether or not to adopt. To date, linkages between learning, advice taking, peer effects and technology adoption remain poorly understood, mainly due to empirical difficulties in directly relating learning to adoption choices (Barham et al., 2014) or isolating peer effects.

The key role of learning in technology adoption is well documented in the literature (e.g., Barham et al., 2014; Foster and Rosenzweig, 2010; Marra et al, 2003), and Foster and Rosenzweig (1996) even argue that acquiring information on the appropriate use of an innovation has particular relevance in agriculture. However, the vast majority of studies do not explicitly account for learning (i.e. utility or profit maximization under perfect information is assumed; Serra et al., 2008). Those that do, either account for the influence of learning by simply including proxy variables (e.g., Läpple, 2010; Genius et al., 2006) or assuming Bayesian learning rules (Feder and O'Mara, 1982). There is evidence in the literature that economic agents do not follow Bayesian learning rules, and tend to ignore previous information and overreact to new information or vice versa (Barham et al., 2014; Gans et al., 2007). However, few studies have formally tested the relationship between learning and technology adoption.

In relation to formal advice, advisory and extension services are seen as the connection between research and changes in the individual farmer's behaviour (Birkhaeuser et al 1991). That is, agricultural extension programmes are targeted to improve productivity through provision of training and the promotion of new technologies (Evenson, 2001). While this importance is widely acknowledged in the literature, most technology adoption studies do not formally account for the impact of extension services or others rely on proxy variables (e.g. Burton et al 2003). While there is a relatively large literature on advice taking outside the agricultural economics literature (e.g. Yaniv and Kleinberger (2000) or see Bonaccio and Dalal (2006) for an overview of this literature), very few studies have measured advice taking in an agricultural context. One exception to this trend is Barham et al (2016) who measure farmers' cognitive ability and receptiveness to advice and examine how these characteristics impact the speed of adoption of GM corn seeds. They find that receptiveness to advice does not necessarily speed adoption. For example, for fast learners being receptive to advice slows technology adoption, while it speeds the adoption decisions of slow learners.

As mentioned above, other farmers are known to play an important role in providing information, thereby reducing information gathering costs, but they can also exert peer pressure (e.g., Läpple and Kelley, 2013; Rehman et al., 2007). In addition, a number of studies have demonstrated a neighbourhood effect in technology choices (e.g., Holloway and Lapar, 2007; Läpple and Kelley, 2015), where neighbourhood is defined in terms of spatial proximity. However, spatially coordinated decisions can also happen without direct farmer interactions, for example due to unobserved favourable conditions that are spatially concentrated (Lewis et al., 2011), which reveals the empirical difficulty in identifying a peer effect with field data.

This study contributes to the literature by using experimental methods to assess the effect of learning ability, peer influences and advice taking on technology choices.

3. Methodology

As previously mentioned, we employ laboratory experiments that measure the learning ability and the responsiveness to formal and peer advice and we link these measures to adoption choices.

Our experiment consists of three parts. Part one assesses adoption choices and innovativeness of participants. Participants had to indicate how many of a set of ten technologies they owned and for how long or if they intend to invest in the technology in the near future if they don't own it. In addition, innovativeness was measured by a set of six statements.

Part two is the "real experiment" and contains of three games relating to learning, advice taking and peer influence. In these games we built upon an experiment originally designed by Harvey and Fischer (1997) and recently used by Barham et al (2016). The basic framework of the game is built around cattle disease outbreaks of varying severity, where participants first learn about how many cattle died in previous outbreaks and then make forecasts of how many cattle will die in subsequent outbreaks. In the experiment, coloured circles represent cattle deaths, and circles vary in size and colour, where colours represented disease severity as follows: red signals the most dangerous, green the next most dangerous, purple the next most dangerous and green the least dangerous. Cattle deaths (Y) related to the area (X) and colour of the displayed circle by the following algorithm:

$$Y = \alpha\beta X$$

and

$$X = \pi r^2$$

α is a constant with value 0.001, β equals three when the circle is red, two when it is green, one when it is purple and 0.5 when the circle is blue, X is the area affected and r is the radius (Harvey and Fisher, 1997). The circles were determined by selecting a radius from a normal distribution with mean 120 and a standard deviation of 30.

In game 1 (learning game), participants play 20 rounds where they see a coloured circle, type in their guess of how many cattle died and then receive feedback information. That is, learning ability is measured using a cue-learning task in which participants play multiple rounds and by receiving feedback can learn how various cues translate into different outcomes (Figure 1 in the appendix shows a screenshot of game 1). We measure learning ability by calculating the mean average percentage error (MAPE), which is the mean of the absolute values of the difference between the forecasts and the actual cattle deaths expressed as the percentage of cattle deaths (Harvey and Fischer, 1997).

Next, we measure the responsiveness to formal advice in an advice taking game consisting of eight rounds in which participants first make an estimate after being presented with cues, are then provided with advice, and afterwards they have the opportunity to revise their initial estimate. That is, the advice taking game starts like the learning game, but after participants typed in their forecast, instead of seeing the correct number, they are presented with the estimate of a more experienced person. In this case we used the estimates of someone who played the learning game for 100 rounds, hence representing external advice (similar to Barham et al 2016). Participants had then the opportunity to revise their initial estimate. See figure 2 in the appendix for a screenshot of the advice taking game. As is common in the advice taking literature, we measure responsiveness to advice as the absolute difference between the initial and final judgement expressed as a percentage of the absolute difference between the original estimate and the advice (See, for example, Yaniv, 2004). We also calculate how MAPE scores changed before and after receiving advice.

In the third game, peer influence is measured in a social learning game consisting of twelve rounds. Here participants first make an estimate based on cues then they see the estimates of two other participants and can exchange views with them via online chat, and can revise their initial estimates then. Participants do not have to agree on the same forecast value. See figure 3 in the appendix for a screenshot of game 3. Similar to advice taking, we measure responsiveness to peers by the difference between initial and final judgement expressed as a percentage of the difference between the original estimate and the peer estimate. We estimate this for both peers individually and compare whether participants differ in the responsiveness between both peers. However, initially we only assess how MAPE scores change before and after the online chats.

The final part of the experiment consists of a number of socio-economic and personality questions that are linked to econometric analysis of technology use responses and the experimental outcomes.

4. Data

Laboratory experiment sessions were held in February 2017 at the National University of Ireland, Galway (NUIG). The experiments were advertised in lectures and online registration links were sent to students via email. Overall, 272 students were recruited, and each one participated in one of 19 one-hour sessions. The number of participants in the sessions varied between 7 and 19, while the average number was 14.32.

To encourage participation, a €5 show-up fee was offered, and each of the experimental games was financially incentivised as follows: A correct estimate earned 50 experimental dollars (E$). An incorrect estimate received a payoff equal to E$50 divided by the absolute difference between the estimate and the truth. For example, if a participant estimated that 90 cattle died, while the true death toll was 100, they had the potential to earn E$50 / (100-90) = E$5. The computer randomly chose one decision in each game to count for payoffs. At the end of the experiment, E$ were converted into € at a rate of €1 for every E$3. Over all sessions, participants' earnings (including the show-up fee) varied between €6 and €41, while the average earnings were €14.55.

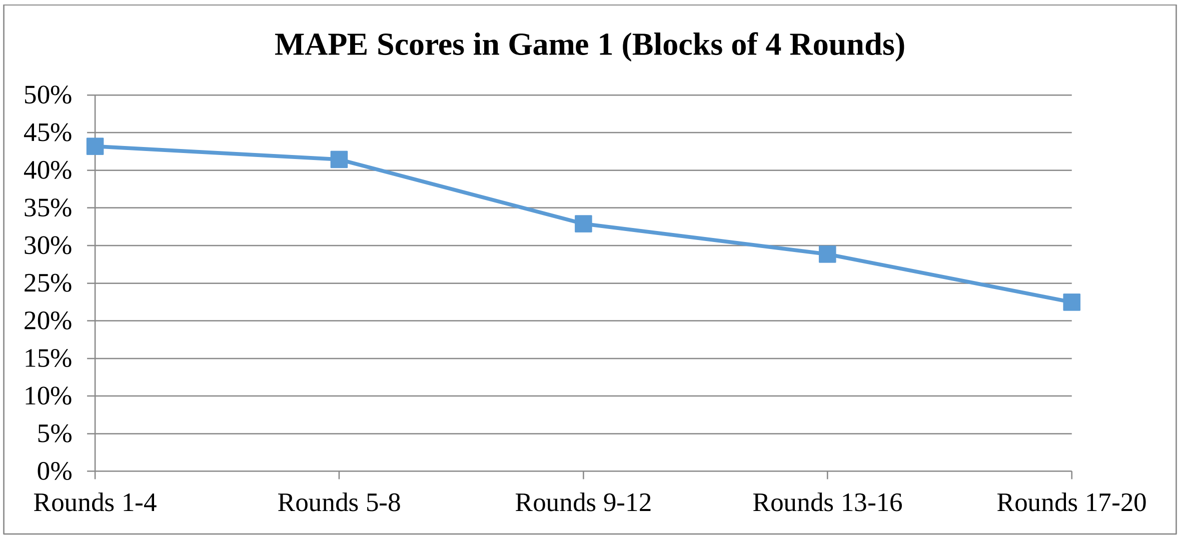
The participants in our sample included 158 males (58.1%) and 114 females (41.9%) who were aged between 18 and 54 years, with a mean age of 20.1 years. All were students at NUIG, and most were Irish nationals (84.6%) in undergraduate education (96.7%) and studying business (56.3%), engineering, manufacturing and construction (19.5%), and humanities and arts (9.6%). The majority of participants were originally from rural areas (63.2%) and during term-time were living in either rented accommodation (51.1%), with a parent or guardian (23.5%), or in a college residence (22.4%). Almost all participants have a weekly disposable income of less than €100 (66.5%) or between €100 and €150 (25.0%), while the most common occupation of their mothers (33.1%) and fathers (26.5%) is Professional, e.g. architect, engineer, GP.

5. Results

All participants own at least one of the 10 electronic devices, while there is no participant who owns all 10. On average, the participants own 4.86 of the devices.

Next, we focus on the results of the learning game. Participants who are better learners are expected to interpret the cues with more precision; hence they are expected to have lower MAPE scores. In addition, we also expect participants to improve at forecasting cattle deaths with increasing experience. Our results reveal that the participants in the experiment had an average MAPE score of 33.8% over all rounds. Figure 4 also shows that their ability to forecast the cattle deaths improved over time, with the average MAPE score decreasing over each of the five blocks of four rounds in the game, from 43.2% over Rounds 1-4, to 22.5% over Rounds 17-20.

Figure 4: MAPE Scores in Game 1 (Blocks of 4 Rounds)



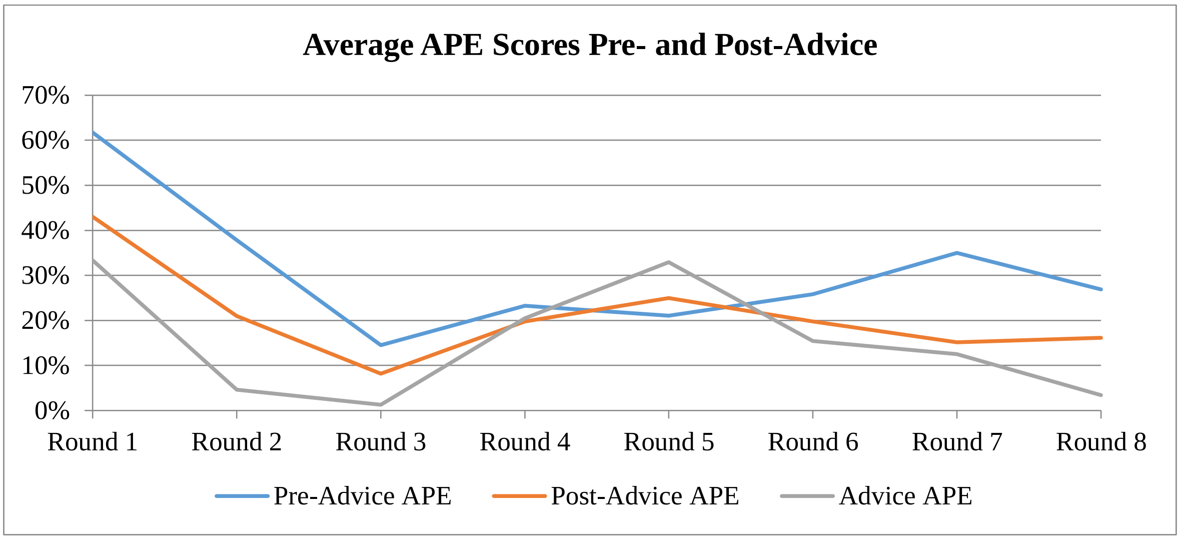
Next, we look at responsiveness to advice. Participants who are more responsive to formal advice are expected to make greater adjustments to their initial estimates after receiving advice. To begin with, we show that the advisor performed better than the majority of participants who, as a result, could improve their performance by following the advisor's estimates. Over the 8 rounds in the game, the average MAPE score of the participants before receiving advice was 30.7%, whereas the advisor's score was 15.5%. Only 10 participants (which equates to 3.7% of the entire sample) performed better than the advisor before receiving advice. After seeing the advisor's estimates, the average MAPE score of the participants fell to 21.0%, indicating that on average participants' performance improved after taking advice. In fact, after receiving advice, 50 participants (18.4% of the entire sample) achieved a lower MAPE score than the advisor. Figure 5 shows the average APE scores for the participants' estimates pre- and post-advice, as well as the APE score for the advice estimates, in each round.[1]

Specifically in relation to responsiveness to advice, participants in the experiment displayed an average responsiveness of 44.4% over all eight rounds in the game, indicating that they placed

[1] We use the term "average APE" to refer to the average of the absolute percentage errors of participants' estimates for a particular decision. In contrast, the term "MAPE" denotes the mean of the absolute percentage errors of participants' estimates across decisions.

slightly less weight on the advisor's estimates relative to their own initial judgements. However, all participants used the advice to at least some extent and no participant discounted the advice entirely; indeed, there was actually one participant who completely followed the advice in every round. Moreover, the responsiveness to advice appeared to be relatively stable across rounds, with an average responsiveness of 46.4% and 42.5% over Rounds 1-4 and Rounds 5-8, respectively. Also, the weight that was placed on the advice did not differ significantly depending on the severity of the disease outbreaks; the average responsiveness to advice the most severe outbreaks (Red circles) was 43.7%, while it was 40.7% for the least severe (Blue circles).

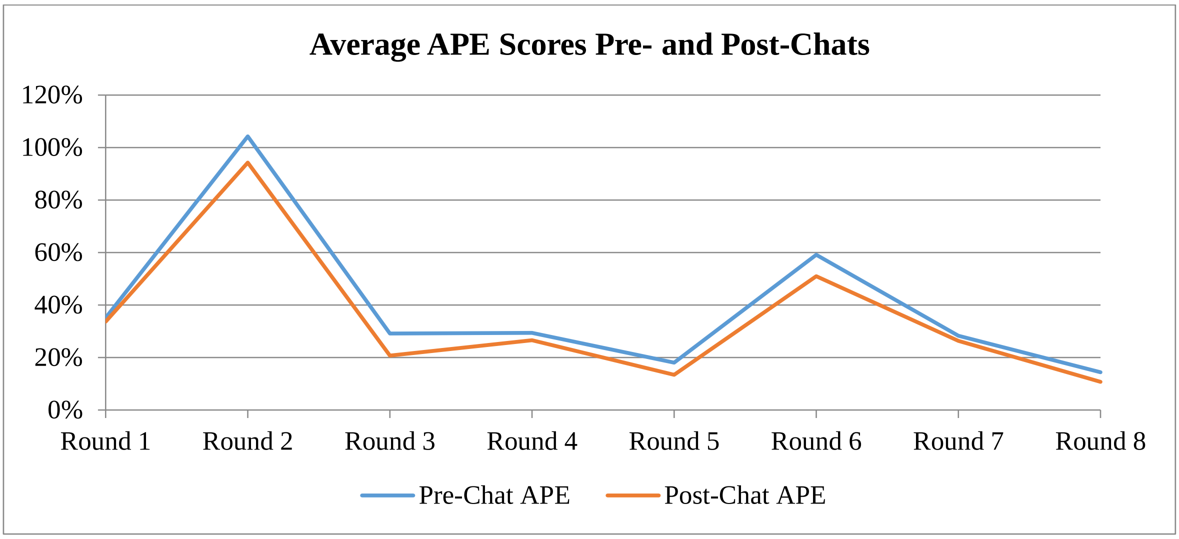
Figure 5: Average APE Scores Pre- and Post-Advice



With regards to specific decisions, the initial estimate, the advice, and the final estimate were all equal in 5.8% of cases, while 5.7% of the time, participants made an adjustment to their initial estimate to have a final estimate equal to the advice. It happened, in 21.6% of cases, that participants gave the same initial and final estimate even though the advice was different. However, the majority of the time, participants gave a final estimate that was somewhere between their initial estimate and the advice (64.4% of the time), and in only a few cases they gave a final estimate that lied outside this interval (2.6% of the time).

In relation to peer advice, the preliminary analysis shows that pre-online chats average MAPE score was 39.7% over the 8 rounds in Game 3 and improved somewhat after the participants engaged in the discussions with their peers (the post-online chats average MAPE score 34.6%). Figure 6 shows the average APE scores for the participants' estimates in each round, both before and after the online conversations.

Figure 6: Average APE Scores Pre- and Post-Chats



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6. Conclusion

This study uses experimental methods to measure learning ability, responsiveness to advice and peer influence and relates these measures to technology choices and innovativeness. The laboratory experiments consist of three games that employ cue learning tasks.

Preliminary results indicate that participants learn when presented with cues, as MAPE scores improve during the learning game. Moreover, our results show that participants improve their performance when following the advice, as they chance their estimates on average by 44 percent.

When interpreting the findings from this article, it is important to keep in mind that these are preliminary results, as data analysis is currently underway. Nevertheless, it is expected that final results will provide important insights in how farmers learn, react to advice and social learning and how this translates into technology choices.

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Appendix

Screenshots of the laboratory experiment.

Figure 1: Screenshot of Learning Game (Game 1)

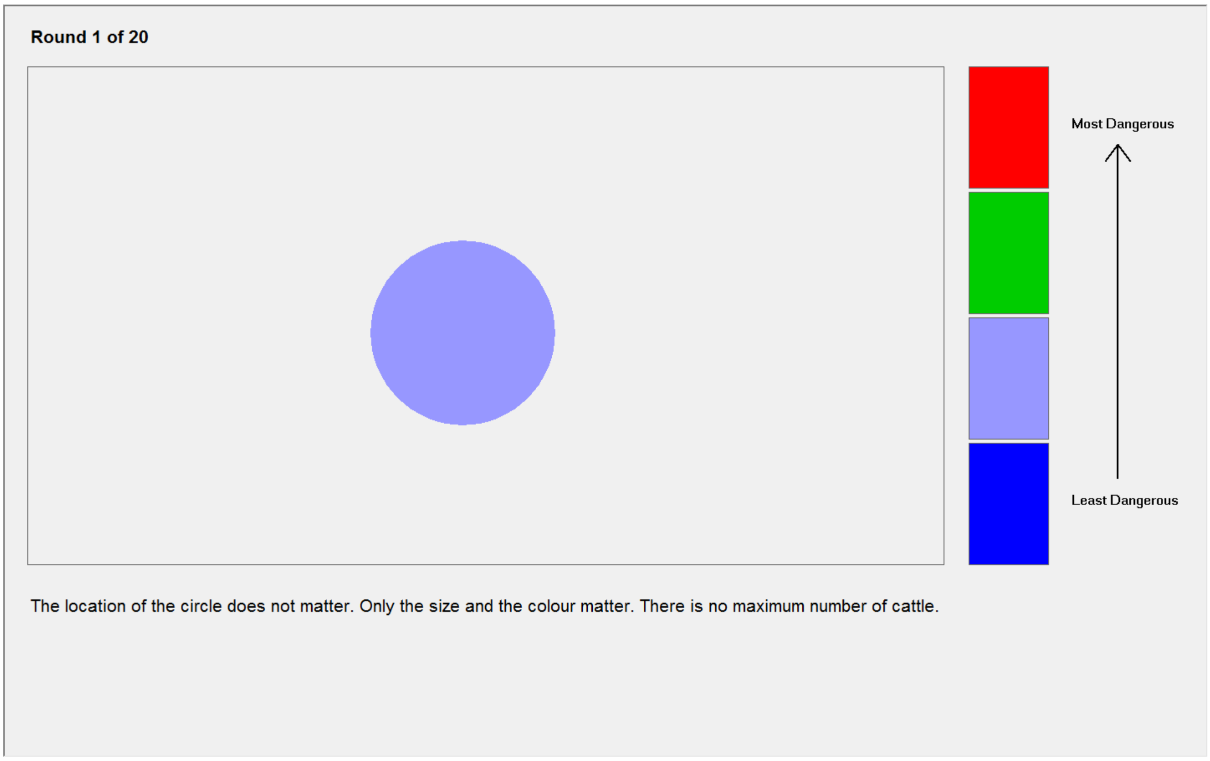

Figure 2: Screenshot of Advice Taking Game (Game 2)

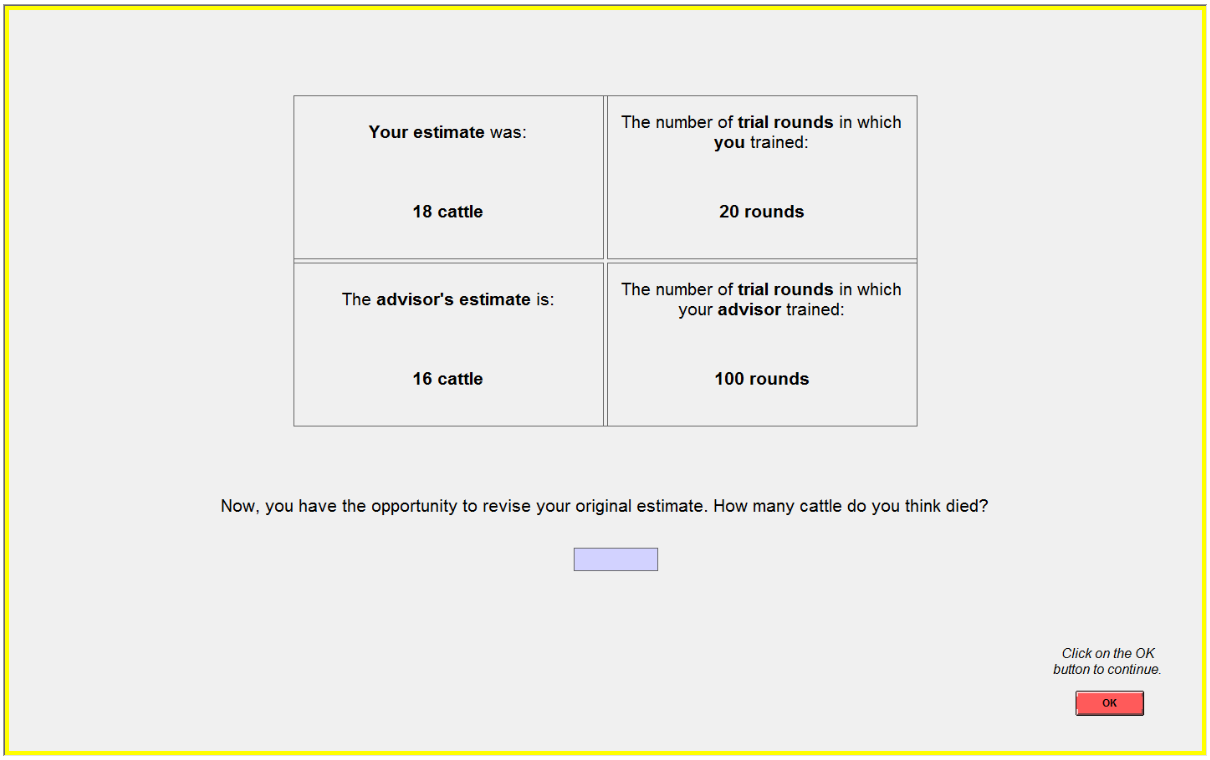

Figure 3: Screenshot of Social Learning Game (Game 3)