Misperceiving the value of information in predicting the performance of others

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February 1, 2005 *

Abstract

Traditional economic and decision-making models allow for "free disposal" of information, which implies a non-negative value for information. Building on previous research on the "curse of knowledge" we explore situations where this might not be so. In three experiments, we document situations in which participants place positive value on information, even when acquiring that information hurts their performance and earnings. In the first experiment, a majority of participants choose to hire informed – rather than uninformed – agents, leading to lower earnings. In the second experiment, a significant number of participants pay for information – the solution to a puzzle – that hurts their ability to predict how many others will solve the puzzle. In the third experiment, we show that the effect is not eliminated by repetition. We discuss implications of our results for the role of information and informed decision making in economic situations.

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* Thanks to seminar participants at Carnegie Mellon and Harvard Business School and participants at the 2001 Economic Science Meetings in Tucson and the 2003 meetings of the Society for Judgment and Decision Making in Vancouver for helpful comments and suggestions.

Introduction

Information is typically assumed to be valuable for decision-making, and in most cases it is. Information helps resolve uncertainty concerning the likelihood and value of outcomes and can also shed light on the likely behavior and strategies of others. Stigler's (1961) seminal analysis of the economics of information spawned a considerable literature exploring the extent to which people can derive rents from possessing information (e.g., Lewis and Sappington, 1997; Osband, 1989; Porter, 1995).

One fundamental assumption underlying almost all economic discussions of information is that more information is (weakly) better for decision-making.[1] Information is rarely thought of as bad, in part because it is widely assumed that decision-makers can ignore information that is not valuable. In most cases, using information will lead to better decisions, and in those in which it doesn't, the information will be ignored.

This "free disposal" assumption may be of questionable validity. Camerer, Loewenstein, and Weber (1989) conducted experiments demonstrating that participants were not able to ignore previously received information when subsequently making a decision and ended up making worse decisions as a result, even though the information they received was accurate. In their experiments, one group of participants made guesses about the earnings of a series of companies based only on information in a report. A second group of participants then traded "assets" (one for each company) with underlying value equal to the average of the first group of participants' predictions for that company. When these traders were given the actual earnings for the

[1] There are some cases in which information has been shown to hurt decision-making. For instance, Fischhoff (1975) demonstrates that knowing the outcomes of events makes people believe that those outcomes were more likely, *ex ante*, than they actually are. Information might also hurt decision makers is when they experience "information overload" with the arrival of too many pieces of information (see, for instance, Earl, 1990). Finally, in laboratory investment decisions Gneezy and Potters (1997) show that more frequent feedback (on the performance of risky investments) leads to more risk-averse behavior and lower expected returns. Work on "herd behavior" also demonstrates that greater information can produce worse outcomes *ex post*, even when the information use is rational, *ex ante* (Banerjee, 1992).

companies (in addition to the reports also received by the original guessers), their trades revealed a bias away from the guesses of the group they were trying to predict, and in the direction of the actual earnings. This phenomenon, which the authors dubbed "the curse of knowledge," indicates that individuals cannot always recover mental states in which they did not possess unhelpful information, even when such recovery would be beneficial. Participants trying to predict the guesses of other participants who did not know the actual earnings should have ignored the actual earnings when making their predictions, but did not do so.[2]

Camerer et al. did not try to measure whether or not participants would have *preferred* to receive the actual estimates. This is especially important since in real economic environments the decision to acquire information is usually endogenously made by economic actors themselves. It might be the case that participants were aware of the negative effect of information but could not ignore it, and hence would have been unwilling to pay for it (or even might have paid to avoid receiving it). Alternatively, they may have not recognized that it was affecting their judgments adversely and might have preferred receiving it. Therefore, while the experiment demonstrated the curse of knowledge, they did not address the question of whether participants given the choice of acquiring information would have fallen subject to the curse.

Some existing experimental evidence suggests that people choose to acquire harmful information. In a review paper, Camerer (1992) reports preliminary experiments in which he auctioned the information used in the Camerer et al. (1989) study, thus allowing subjects the opportunity to state how much they valued, if at all, such harmful information. Though he conducted only two sessions with a total of 18 subjects, a majority of subjects initially stated a positive price. However, with repetition, the tendency to value the harmful information appeared

[2] Camerer et al. also found that market forces reduced the bias: when the "assets" were traded in a market, participants on average were less susceptible to the curse of knowledge than when they simply tried to predict what other participants had guessed.

to dissipate: After the fourth period, only very few subjects gave positive prices in the auction (and some even gave negative prices, indicating they wanted to be paid for acquiring the information). More recently, Charness and Gneezy (2003) show that a majority of subjects choose to receive more frequent information about the performance of a risky asset (and to have the ability to make more frequent changes to their portfolio), even though previous research indicates that such information and discretion lead to lower returns on average (Gneezy and Potters, 1997). However, Charness and Gneezy do not explore whether these particular participants performed better or worse as a result of the more frequent information.[3]

While the above studies suggest that people may value harmful information, neither provides a conclusive demonstration. In this paper, we report experiments that explore the implications of the potentially harmful effects of more information and people's willingness to acquire such information. Like Camerer et al., we document situations in which information produces a "curse of knowledge." We then explore whether people place value on such information, and whether they are subsequently harmed as a result. Finally, we also explore whether such a bias persists with repetition.

Using contexts in which people have to predict the decisions or performance of uninformed others, we find that harmful information is valued positively by our subjects. In a first experiment, we find that a majority of subjects choose to "hire" an informed agent instead of an uninformed one, even though the latter actual make more money due to the curse of knowledge. In a second experiment, we find that almost a third of subjects are willing to pay for information that causes them to make worse predictions and earn less money. Finally, we find that the hiring of informed agents decreases only slightly with repetition.

[3] This is important, since investment decisions by the two (endogenously determined) groups might differ.

Our results are consistent with the notion that people's naïve theories about their use of information parallel economic theories in assuming that more information is good (or at least not bad). While this rule of thumb will most often lead to better decision-making, our studies show that this is not always the case. We conclude the paper by exploring possible implications for economically consequential situations.

Experiments

Participants in our experiments are given the goal of predicting the performance of others in solving a problem.[4] We show that knowing the solution to the problem leads people to make worse predictions about the behavior of those trying to solve the problem. In the first experiment, we find that if people are given the choice of "hiring" an agent that is either informed (knows the solution) or uninformed (does not know it), a majority of participants tie their earnings to the informed agent and end up making less money as a result. In the second experiment, we show that a significant number of people who are given the choice of paying a cost to obtain the harmful information choose to do so. In the third experiment, we show that the tendency to pay for information is not eliminated with repetition.

Experiment 1: Hiring "cursed" agents

Experimental Design

One large session was conducted with 166 students from Carnegie Mellon University and the University of Pittsburgh. Participants showed up to a large auditorium and were told that

[4] The complete dataset from all three experiments is available on the author's website: www.andrew.cmu.edu/~rweber.

they would be paid based on their decisions in the experiment.[5] Upon arriving, they were seated and received written instructions, which differed by role. Roles were randomly assigned by randomly distributing instructions.

<u>Chains Puzzle</u>: You have four chains of three links each, shown below. Your challenge is to take the four chains and form them into one continuous ring while breaking and re-connecting no more than three links. Which three (or less) links do you break and re-connect? When you have the answer, draw arrows to each of the links, and have the experimenter verify your answer.

<u>Boxes Puzzle</u>: By repositioning only two of the matches in the following picture, how would you create four squares instead of five? Remember that the squares may be repositioned but the new squares will be the same size as the old ones. When you have the answer, draw the new arrangement of matchsticks, and have the experimenter verify your answer.

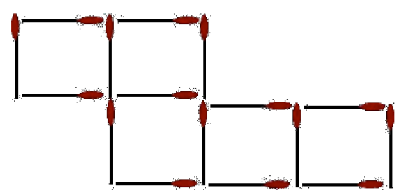

Figure 1. Puzzles used in experiment 2 ("chains" and "boxes")

Each participant was in one of four roles: *Solver*, *Informed Predictor, Uninformed Predictor*, or *Chooser*. Each Solver was given one puzzle to solve. The puzzle was a simple analytical problem in which participants needed to generate an insight to figure out the solution. We used two different puzzles: the "boxes" puzzle and the "chains" puzzle, shown in Figure 1.[6]

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[5] The experiment was the first part of several tasks that the participants completed (which included another experiment and filling out questionnaires). Since this was the first task in which they participated, and since they were not told about the other tasks, it is unlikely that any of the other tasks affected performance in this one.

[6] The solution to the "Chains" puzzle involves opening all three links on one of the segments and using these three links to connect the remaining segments. The solution to the "Boxes" puzzle involves repositioning the second (from right) match in the top row and the middle match in the bottom row to form a new box in the top row, third column (this leaves two boxes in the top row (1st and 3rd columns) and two in the bottom row (2nd and 4th columns)).

Roughly half the participants in each role had the chains puzzle, and the other half had the boxes puzzle (see Table 1 below).

Solvers were paid based on how quickly they solved the puzzle. Specifically, they were told that if they solved the puzzle immediately they would receive \$6. The amount they received went down by one cent for each second they spent solving the puzzle. If they did not solve the puzzle after 10 minutes (600 seconds) then the payment was equal to zero. Fourteen participants were in the role of Solver.

Both types of *Predictors* were told that they would be paired with one randomly selected Solver. Predictors' task was to predict how long the Solver would take to solve the puzzle. Predictors were shown the puzzle. They were rewarded for predicting longer times (i.e., waiting longer), but were penalized for exceeding the actual time it took the Solver to solve the puzzle. Specifically, Predictors received one cent for every second they predicted the Solver would take, but that payment fell to zero if their prediction was longer than the actual time it took the Solver. In other words, Predictors maximized their payoffs when they predicted exactly how long it took the Solver to solve the puzzle, but not longer.[7]

Ninety-nine participants were in the role of Predictor. Fifty of these predictors were told the solution to the puzzle (*Informed Predictors*) and forty-nine were not (*Uninformed Predictors*). We designed the incentives faced by Predictors to very roughly mimic those that would be faced by someone trying to decide how long to wait to introduce a new invention to the market, where there is a threat that a competitor may also come up with the invention, and if so

[7] We used this kind of scoring rule (rather than, for instance, a quadratic one) because of its simplicity and ease in explaining it to subjects. Since we do not know precisely what participants' subjective distributions for completion times are or their risk preferences, we cannot say that a subject's response measures the expected completion time. However, since we are primarily interested in comparing estimates by the two kinds of Predictors, it is not unreasonable to assume that subjects guessing lower completion times expect faster completion. Moreover, we also rely on the actual earnings of the two kinds of Predictors as a measure of their performance.

may introduce it to the market first. In such cases, it often pays to be the first mover, but delaying introduction of the invention to the market allows one to refine its design. If people in this situation suffer from the curse of knowledge, then one would expect those who are aware of a key insight to exaggerate their competitors' progress and hence to introduce their own product too early. Thus, our first prediction was that Informed Predictors would make less money than Uninformed Predictors.

Role	Boxes	Chains	Total
Solvers	8	6	14
Choosers	27	26	53
Uninformed predictors	23	26	49
Informed predictors	27	23	50
Total	85	81	166

Table 1. Number of participants by puzzle and condition

Another fifty-three of the participants were in the role of *Chooser*. Each Chooser's task was to decide whether to tie their payment to that of an Informed or Uninformed Predictor. The problem faced by Choosers is similar to that of a principal in the invention problem just described who must hire an agent to predict how long it will take competitors to come up with the idea for the invention. Choosers were first asked to predict the average payoffs for the two different types of Predictors. Then they were told that their payment would be equal to that of one randomly chosen Predictor, but they could pick whether that Predictor would come from the set of the Informed or the Uninformed. Our second, and main, hypothesis is that Choosers will misjudge the benefit of information and will guess that Informed Predictors will make more money and will select an Informed Predictor as their "agent."

Table 1 presents the number of participants for each role and for each puzzle.

Results

Six of fourteen Solvers (43 percent) were able to solve the puzzle. The remaining eight Solvers worked on the puzzle the full ten minutes and did not solve it. The average time spent for all Solvers (including the ones who did not finish) was 7 minutes and 2 seconds (SD = 3:54), and did not significantly differ between the boxes (mean = 7:20, SD = 4:14) and chains (mean = 6:37, SD = 3:47) puzzles ($\underline{t}(12) = 0.32$).

Predictors, on average, predicted that Solvers would require 4:08 (SD = 2:32) to solve the puzzle. Both Informed and Uninformed Predictors underestimated Solver solution times but Informed Predictors did worse, and predicted that Solvers would solve the puzzle more quickly (mean = 3:36, SD = 2:28) than did Uninformed Predictors (mean = 4:41, SD = 2:30). This difference is significant at the $p < 0.05$ level ($t(97) = 2.17$). As a result, Informed Predictors earned significantly less money on average (mean = \$1.45, SD = \$0.84) than Uninformed Predictors (mean = \$1.76, SD = \$0.80) ($p < 0.1$, in a two-tailed test ($t(97) = 1.88$)).

The above results demonstrate the curse of knowledge. Informed Predictors did a worse job predicting the performance of Solvers than did Uninformed Predictors, and ended up making less money as a result. Given this, unbiased Choosers should believe that Informed Predictors are likely to earn less money that Uninformed Predictors, and should select Uninformed Predictors as their "agents."

This is not the case. Choosers tended to believe that Informed Predictors would earn more money than Uninformed Predictors. Chooser's average estimates of earnings for Informed Predictors were \$3.43 (SD = 1.93) and for Uninformed Predictors they were \$2.77 (SD = 1.51). The average within-subject difference between these estimates (\$0.65) is significantly different from zero ($t(52) = 2.26$, $p < 0.05$). Of the 53 Choosers in the experiment, 28 (53 percent) gave an earnings prediction that was higher for the Informed Predictor than the Uninformed Predictor, 17 (32 percent) guessed that Uniformed Predictors would have greater earnings, and 8 (15 percent) guessed equal earnings for both types of predictors.[8]

Finally, Choosers' expectations that Informed Predictors would earn more money are reflected in how they chose to have their earnings determined. The majority of Choosers (33 of 53, or 62 percent) chose to tie their payoffs to informed Predictors. This differs significantly from 50 percent ($p < 0.1$ in a two-tailed Binomial test using the normal approximation with adjustment for continuity ($z = 1.65$, see Siegel and Castellan, 1988)).

The results of Experiment 1 provide clear support for our hypotheses. Participants were clearly subject to the curse of knowledge: Informed Predictors did significantly worse than Uninformed ones in predicting the amount of time it would take solvers to complete the puzzle. More importantly, Choosers' guesses exhibited the opposite pattern – they tended to believe that Informed predictors would do better. In addition, when given the choice of selecting an agent to determine their earnings, a majority of Choosers selected agents that were Informed rather than Uninformed, leading to lower payoffs.

Experiment 2: Paying for cursed knowledge

In Experiment 2 we provide a stronger test of the phenomenon and test its robustness using a different prediction task. Specifically, we explore directly whether people are willing to pay to acquire harmful information.

[8] The misprediction by Choosers is even more dramatic when judged against the standard of accurately predicting earnings. Choosers on average guessed that both kinds of Predictors would make more money than they actually did. However, Choosers overestimated the earnings of Informed Predictors (mean overestimation = \$2.09, SD = \$1.94) by more than they did for Uninformed Predictors (mean overestimation = \$1.06, SD = \$1.51). The average within-subject difference between the degree of overestimation for Informed and Uninformed Predictors (\$1.03) is significantly different from zero ($t(52) = 3.54$, $p < 0.001$).

Experimental Design

Participants in two sections of an introductory business class at Carnegie Mellon (n = 66) viewed three video clips. In each clip, two nearly identical images alternated appearing on the screen, each one appearing for about one second. The two images alternated for about 20 seconds. In between each appearance of the images, there was a very brief flash in which the screen was completely white. The two images differed in one important aspect. For instance, one set of images is pictured in Figure 2. Before reading on, try to distinguish the difference between the two images.

These video clips have been previously used to demonstrate "change blindness" – the difficulty most people have noticing changes or inconsistencies in visual perception, even when these are as substantial as in Figure 2 (Rensink, O'Regan, and Clark, 1997; Simons and Levin, 1997). Therefore, we predicted that participants would have a difficulty noticing the differences.

Figure 2. Sample of images used in experiment 1

While most people have a hard time noticing the differences between the paired images, they are quite obvious once they are highlighted. For instance, notice that the two images in Figure 2 are identical except that the one on the right has the shadow cast by the helicopter below the jeep, while the one on the left does not. As with previous experiments on the curse of knowledge, we predicted that participants who were informed of the difference would find it very difficult not to notice it and would tend to overestimate the extent to which other participants would notice the difference.

For each video clip (each pair of images), participants were first told that their goal was to identify the difference between the two images. Specifically, they were instructed that, "There is one difference between the pictures you will see in each clip. Look to see if you can spot the difference." Participants were also asked to predict what percentage of their classmates who did not know the difference would be able to spot it. Participants were paid for the accuracy of their predictions. If a participant's guess was within 2 percentage points of the actual percentage, then he or she would receive $10. If the guess was 3, 4, or 5 percentage points away, the payment was $5. Guesses off by more than 5 percent earned nothing. Participants repeated this task three times (once for each video clip) and their earnings were summed across all three video clips. Participants were not given any feedback until after the experiment.

Across the three clips, participants experienced each of three following information conditions:

- In the *Uninformed* condition, participants were not informed of the difference between the two pictures. They simply watched the video clip and then made a prediction.
- In the *Informed* condition, participants' written instructions informed them, in bold type, of the difference.[9]
- In the *Choice* condition, participants were given the option of finding out what differed between the two images. Each participant received an envelope that revealed inside what

[9] For instance, for the clip with pictures represented in Figure 2, participants in the Informed condition were told, "CLUE: The helicopter's shadow disappears."

the difference was. However, participants were told that by opening the envelope they would sacrifice a $0.50 bonus.

	Clip 1 – **“Statue”**	Clip 2 – **“City”**	Clip 3 – **“Chopper”**	Number of participants
Sequence 1	Uninformed	Informed	Choice	25
Sequence 2	Informed	Choice	Uninformed	20
Sequence 3	Choice	Uninformed	Informed	21

Table 2. Number of participants by sequence of conditions

Each participant experienced all three information conditions. Table 2 presents the three sequences in which participants experienced the information conditions and the corresponding sample sizes. To minimize any effect of curiosity, all participants were told that they would be shown all three clips again and informed about the difference between the images at the conclusion of the experiment.

Results

When participants were uninformed about the change, 20 percent of them correctly identified the change, and this did not differ by video clip ($F(2,63) < 1$, ns). Our experiments, therefore, replicated the finding that the changes are difficult to detect.

As the results in Table 3 indicate, uninformed participants on average guessed that 30 percent (SD = 26 percent) of their uninformed peers would spot the change; they earned an average of $1.21 (SD = $2.49). When participants were informed about the difference in the two pictures, they guessed that 58 percent (SD = 33 percent) of their uninformed peers would spot the difference, and earned an average of \$0.45 (SD = \$1.69). The average within-subject difference between guesses in the Informed and Uninformed conditions is significantly different from zero for both guesses ($t(65) = 6.28$, $p < 0.001$) and payoffs ($t(65) = 2.19$, $p < 0.05$). These results are consistent with the curse of knowledge: Participants who are told the difference between the two pictures are worse at predicting how frequently other participants who do not know the difference will be able to find it.

Information condition		Mean prediction	Standard deviation	N
Uninformed		30.1 %	25.6	66
Informed		58.2 %	32.7	66
Choice		40.6 %	29.5	66
Choice (unopened)	(71%)	34.6 %	29.0	47
Choice (opened)	(29%)	55.4 %	25.8	19

Table 3. Predictions pooled by information condition across sequences

Among uninformed participants, some figured out the difference on their own (13 of 66). Since they did so before making their guesses, we might expect them to be more likely to correctly infer how difficult it is to notice the difference. This was not the case. For participants in the Uninformed treatment who figured out the difference, the mean guess was 63.4 percent, which is slightly higher than the mean guess in the Informed condition. Therefore, participants who figured out the difference on their own were no less likely to fall victim to the curse of knowledge than those who are told of the difference. Interestingly, the mean guess by uninformed participants who did not figure out the difference was 21.9 percent, which is very close to the actual percentage (20 percent).

The important question for our main hypothesis deals with what participants will do when given the choice of being informed or uninformed. That is, will they choose to pay to acquire harmful information? This is exactly the decision faced by participants in the Choice condition. When given the choice of whether to learn the difference between the two pictures before seeing the clip and making their guess, 19 of 66 participants (29 percent) chose to open the envelope and become informed. These participants all sacrificed $0.50 for doing so.

The pattern of earnings among participants in the Choice condition similarly reflects the curse of knowledge. The 47 participants who chose not to open their envelopes guessed, on average, that 35 percent (SD = 29 percent) of their uninformed peers would see the difference, while the 19 participants who chose to pay $0.50 to become more informed guessed, on average, that 55 percent (SD = 26 percent) of their uninformed peers would see the difference. This difference is significant ($t(64) = 2.71$, $p < 0.01$). As a result, those who chose to remain uninformed earned an average of $1.49 (SD = $3.10), whereas none of those who chose to open their envelopes earned anything. This difference is also significant ($t(64) = 2.08$, $p < 0.05$).

Overall, the results support our main hypotheses. Participants are clearly better off if they are not informed (as in Experiment 1), but a significant proportion choose to pay a $0.50 fee to acquire information that harms their performance. While there are some interesting interactions when sequence effects are examined, none of these contradicts our main result.[10]

[10] Analyzing the results by sequence reveals two substantive differences. First, participants in the Choice condition in Sequence 1 are slightly more likely to make better predictions when they open the envelope (mean guess: 41.8 percent) than when they do not (49.8 percent). However, participants in every other comparison do better when they are uninformed (mean guesses: 29.9, 29.1, 33.1, 25.6, and 27.6 percent) rather than informed (mean guesses: 59.3, 68.7, 71.4, 34.0, and 46.7 percent). Second, participants in Sequence 3, for whom the Choice condition is the first in the experiment, are less likely to open the envelope (4.8 percent do so) than participants in other sequences (40.0 percent). There are at least three possible explanations. First, it is possible that participants do not want to open the envelope because they want to see if they can spot the difference on their own, a tendency which should act against our hypothesized effect. A second possibility is that participants were overconfident in their ability to detect the change, which also works against our hypothesis. The last possibility is that participants without prior experience

In Experiment 3, we provide a final test of the robustness of the main result. We have subjects make the same kind of choice as in Experiment 1 –hiring an informed vs. an uninformed agent – but also make the informed agent more costly, as in Experiment 2. We also have subjects perform the task over several periods, with feedback.

Experiment 3: Learning not to pay for the curse

Experimental Design

In this experiment, we combined elements from the first two experiments and added repetition to explore the effect of feedback on the tendency to value information that results in the curse of knowledge. We used the task and video stimuli from the second experiment and, as in Experiment 1, put subjects in a situation where they were hiring "agents" to make predictions.

In the experiment, subjects in two sections of a large introductory business class at Carnegie Mellon (n = 59) were told about the task posed to subjects in Experiment 2: guessing what percentage of people would spot the change between two pictures. To help them understand the task, they were shown the first of the three clips from Experiment 2. They were not told what changed or how many people saw the change. Instead, they were told that there had been two types of guessers in Experiment 2: "Group I" and "Group U." Subjects were told that members of Group U did not know what changed before they watched the clip and made their guess and that members of Group I were told what changed before they watched the clip and made their guesses.

Subjects were then faced with a decision task, which they performed for six rounds. In each round, they had to select an "agent" from Experiment 2 and would receive the same payoff

with this task do not believe that knowing the difference between the images will increase their earnings beyond the $0.50 cost, but, after one experience, change this belief. This suggests that the effect could worsen with experience.

as that subject received. They made the choice by selecting from a stack of sheets containing the guesses (and monetary earnings) of subjects in experiment 2. Their choice was whether to select a guesser from a stack containing only guesses from Group I subjects or from one containing guesses only from Group U subjects. There was a $0.10 fee for choosing a guesser from Group I. After selecting, subjects were shown the guess made by the randomly selected subject about what percentage of people would see the change, and saw their payoff from that choice.

There was a slight difference between rounds 1 and 2 and rounds 3 through 6. After making their choices in rounds 3 through 6, participants were given feedback with one additional piece of information: the true percentage of those seeing the change. This was information was provided to see if an even stronger form of feedback could correct the bias if the initial feedback did not.

At the end of the experiment, two out of the six rounds were randomly selected to determine payoffs for the experiment. Even though the monetary payment a subject received only depended on two out of the six choices, subjects did not know which ones these would be until the end.

Round	1	2	3	4	5	6	Total
Percentage choosing I	22%	37%	32%	34%	27%	19%	29%

Table 4. Percentage of subjects choosing the informed guesser

Results

Table 4 presents the results across six rounds. Each entry in the table represents the percentage of subjects in that particular round, who selected an agent from Group I. As the results indicate, subjects chose to draw their earnings from the informed group 29 percent of the time, and this percentage did not change very much over the course of the six rounds. While there appears to be some variation between rounds and a slight downward trend, the percentages in the first and last rounds are very similar.

Naturally, because uninformed guesses were more accurate, those who chose Group I on average earned less than those who chose Group U. The mean earnings for rounds in which subjects chose from Group U were \$1.17, whereas mean earnings from Group I were \$0.40 less the \$.10 cost of choosing I, or \$0.30. Therefore, as in Experiment 2, we find that roughly a third of the time people opt to pay for harmful information.

	All periods		Periods 3-6	
	Logit	Conditional fixed-effects logit	Logit	Conditional fixed-effects logit
Round	-0.064 (0.069)	-0.078 (0.076)	-0.238 (0.132)*	-0.302 (0.151) **
Constant	-0.696 (0.264)***		0.110 (0.594)	
N	354	258 (43)	236	140 (35)
Log likelihood	-211.22	-102.07	-138.20	-50.08

Table 5. Effect of round on behavior

A more rigorous test of the hypothesis that the bias decreases with repetition is evident in Table 5. This table reports logistic regressions testing whether the frequency with which subjects choose an agent from Group I decreases across periods. The first two regressions use data from all rounds, while the last two use data only from rounds 3-6, which included more feedback. The second regression in each pair includes subject fixed effects.[11] The regressions including all periods reveal no significant decrease across rounds in the frequency with which subjects chose from Group I. If we look only at rounds 3-6, we find a significant decrease for

[11] The number of independent observations in these two regressions (in parentheses) is smaller than 59 because several subjects made all their choices from one of the two groups.

these periods, indicating that providing subjects with information about the true percentage (rather than just about the guess made by their "agent" and the payoff), leads to some elimination of the bias. However, even after four rounds of such feedback, a significant proportion of subjects continue to pay for the harmful information.

Discussion

Taken together, our experiments demonstrate that participants exhibit the curse of knowledge when trying to predict the performance of others. In the first two experiments, participants who were given the solution to a problem or discovered it on their own tended to make biased predictions about how easy it would be for others to obtain the solution, leading to lower performance and earnings. This result is consistent with previous work demonstrating the curse of knowledge.

We also demonstrate that people are generally unaware of this bias and believe that more information will be at least weakly better. We observe this most strongly in experiment 1, in which a majority of participants (62 percent) opt to "hire" an informed agent and end up making less money as a result. The belief that information is beneficial is also reflected in their estimates of the earnings of the two kinds of agents. In Experiments 2 and 3, we find that roughly 30 percent of subjects choose to acquire such information, even when they have to pay for it. Moreover, Experiment 3 reveals that this bias decreases only slightly with repetition.

Of course, we demonstrated this bias using decision tasks with very specific characteristics. In our experiments, the problem to be solved required obtaining an insight or noticing something hard to see. Prior research has shown that outcome feedback (in this case the solution to the problems) biases people's predictions of others for insight problems, but not for all other types of problems (Hoch and Loewenstein, 1989). For example, being told the answers to trivia problems often helps one to predict whether others will be able to answer those problems correctly because, if the answer is surprising, one will recognize that few people will get it right. Therefore, one should be cautious of generalizing our results to too wide a domain of problems and tasks. Our results also do not address the question of whether more information will generally be better when decision makers are not trying to predict the performance of others, or when the underlying problem is not one in which insight plays a key role. Our main result should be viewed more as a demonstration of the combined facts that accurate information can, in situations with some key characteristics, be harmful and that a significant percentage of people are not aware of when this is true.

There are many consequential economic and organizational situations with the key characteristics of our experiments. Experiment 1 serves as a metaphor for one such situation, in which a firm is trying to figure out how quickly or easily a competitor will develop a product or innovation requiring a key insight. Our results suggest that, in such situations, knowing more about the insight associated with the product or innovation may lead to worse predictions, but that decision makers may delegate those decisions to those who know more. A similar problem surrounds the question of who should write product documentation or instruction manuals. Our results suggest that the people who know the most about the product or the topic may over-estimate the ease with which others will be able to understand the necessary information. It has been shown, for example, that experts on the use of a telephone headset were worse than people with intermediate levels of experience when it came to predicting how long it would take novices to learn the basics of using the headset (Hinds, 1999). Therefore, the most informed or most knowledgeable individuals may be worse at writing such documentation than someone who is less informed, but there may be a common bias to assume that those with more information will be the best at writing such documents. Both of the above examples would be similar to our experimental result that people tend to hire the wrong kind of agent to try to predict how much others know or how easily they will solve problems.

Final comments

Stigler's seminal paper on the economics of information initiated an extraordinarily productive line of research on the "new economics of information," which has encompassed phenomena such as signaling, adverse selection, asymmetric information in bargaining and "herd behavior." We hope that the work presented here will become part of a "new new" economics of information that draws on psychological research to revise some of the strong, unrealistic assumptions that economists typically make about the ways in which people use information.

Some of this new research calls into question conventional assumptions about information processing, such as the idea that information can be freely disposed of or that people update probabilities in a fashion consistent with Bayes' rule. For example, people exhibit "hindsight bias" (Fischhoff, 1975) that is, in a way, a within-person version of the curse of knowledge; people overestimate their own ability to have predicted events which they know have taken place. They have a difficult time reverting back to their original beliefs after evidence on the basis of which they updated those beliefs is discredited (e.g., Ross, Lepper and Hubbard, 1975). And in some situations, they seem to underweight base-rates in forming expectations of future events (e.g., Bar-Hillel, 1990).

Another line of research challenges the conventional assumption that people process information in an impartial fashion. For example, research on the self-serving bias shows that people unconsciously and without deliberate intent interpret information in a fashion that is favorable to themselves (Babcock and Loewenstein, 1997). Research on the "confirmatory bias" shows that people behave in a "super-Bayesian" fashion, dismissing evidence that contradicts their preexisting beliefs and overweighing evidence that confirms them (e.g., Lord, Lepper and Ross, 1979; Rabin & Schrag, 1999).

Yet a third line of work focuses on the non-controversial idea that information can constitute a source of utility apart from its role in securing desired material outcomes. Several existing economic models incorporate utility from information – e.g., from anticipation of future outcomes (Loewenstein, 1987; Caplin and Leahy, 2001), beliefs about one's own self-worth (e.g., Koszegi, 2001; Loewenstein, 1999), perceptions of fairness (e.g., Rabin, 1993), and from feelings of identification with groups (Akerlof & Kranton, 2000).

Clearly, there is more to be learned about the economics of information.

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