Using Advice from Multiple Sources to Revise and Improve Judgments

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Abstract

How might people revise their opinions on the basis of multiple pieces of advice? What sort of gains could be obtained from rules for using advice? In the present studies judges first provided their initial estimates for a series of questions; next they were presented with several (2, 4, or 8) opinions from an ecological pool of advisory estimates (Experiment 1), or with artificial advice (Experiment 2); finally they provided their revised estimates. Descriptive analyses of their revision process revealed that they egocentrically trimmed the opinion sets such that opinions distant from their own were greatly discounted. Normative analyses suggested that they gained substantially from the use of advice, though not optimally, due to their self-centered utilization of the advice. The results are discussed in connection with to theories of belief revision and attitude change, with an emphasis on decision makers' strategies for coping with conflicting opinions and the appropriateness of discounting distant or dissenting opinions. Prescriptive implications for the utilization of advice are also considered.

Keywords: Judgment under uncertainty, combining opinions, utilizing advice, decision making, egocentric judgment

It is common practice to solicit other people's opinions prior to making a decision. An editor solicits two or three qualified reviewers for their opinions on a manuscript; a patient seeks a second opinion regarding a medical condition; a consumer considers the "word of mouth" of a dozen people for guidance in the purchase of an expensive product. All these situations involve decision-makers in the task of combining multiple opinions to revise their own (Sniezek & Buckley, 1995). The rationale for soliciting advice is straightforward. Real-life decisions are often not self contained – the range of possible options for choice and their descriptions are often not fully specified. Decision makers solicit advice to gain information, help them frame their decisions, refine their preferences, and create options beyond those available to them at the moment. At times, people may seek advice for other reasons, such as self-affirmation or for sharing responsibility due to concerns about accountability to others (Kennedy, Kleinmuntz, & Peecher, 1997). Such social reasons are also rooted in the belief that getting advice should ultimately be beneficial to the decision process.

We explore the following paradigmatic situation here. A decision-maker first forms an initial opinion about some issue. Then she receives multiple advice (e.g., two to eight opinions generated by other judges) on the basis of which she revises her initial opinion. We investigate two fundamental issues – first, the influence of advice on decision-makers' final opinions and the *revision rules* they employ in combining the opinions; and second, the *benefits* of using advice, specifically, both the potential and the actual gains that could be obtained by using advisory opinions.

In these experiments we consider perhaps the simplest form of advice use, namely getting pieces of information (numerical estimates) from outside parties and using them to update one's own view. As simple as it is, numerical advice has an important function in decisions. Experts such as physicians, weather forecasters, and business consultants often communicate their forecasts and uncertain estimates to others facing decisions. In addition, the use of numerical estimates has certain methodological advantages, primarily the ability to quantify straightforwardly the influence and benefits of using the advice (i.e., participants' revision policies and accuracy gains).

A key issue in integrating advice from multiple sources involves the difficulty of dealing with conflicting advice (Sniezek & Buckley, 1995). Dissenting opinions pose a challenge to the decision-maker, as when two advisors recommend one course of action, while a third one recommends another (Harries, Yaniv, & Harvey, 2004). On top of advisor disagreement, decision-makers need to reconcile potential disagreements between the advisors' and their own opinions (i.e., self vs others).

The present research seeks answers to the following questions: How do people resolve potential conflicts between their own opinions and a sample of advisors' opinions? How do they weigh a dissenter's opinion vis-à-vis the "consensus opinion"? What might be a good strategy for combining multiple pieces of advice? The main contribution of this research is in bringing together three issues. First, it involves multiple (rather than single) advice. Second, it is focused on the process of revising one's *prior* opinion based on advice (rather than purely combining estimates). Third, we conducted a parallel investigation of descriptive and normative issues, where the normative results provide useful benchmarks for assessing decision-makers' performance. This allows us to assess how good or adaptive people's revision rules are.

Our findings lead us to several conclusions. We find that decision-makers gain substantially from the use of multiple pieces of advice (two to eight), yet their gains are not optimal, due to their self-centered utilization of the advice. The findings suggest that in combining sets of three to nine opinions altogether (i.e., their prior opinions and the advice), participants selectively weight the opinions that are close to their own, while ignoring those that are distant from their own prior opinion. We call this egocentric trimming. This result contrasts with our normative analysis (based on the same data), which suggests that trimming is indeed a good strategy that could be used

beneficially to improve accuracy, as long as it is conducted *objectively* rather than egocentrically (consensus-based trimming).

Aside from their practical implications for realistic decision making, these results carry a deeper theoretical message. A fundamental question in the literature in recent decades has been how adaptive or rational human behavior is, in light of research suggesting flaws in intuitive judgment and decision making. The process of giving and receiving advice could be viewed as an adaptive social decision-support system that helps individuals overcome their inherent limitations (cf. Schotter, 2003) by proposing new alternatives, different frames, and disconfirming information.

The Influence of Advice: The Process of Revising Opinions

How might people revise their opinions on the basis of advice from others? The task seems taxing, both cognitively and emotionally, as decision-makers need to decide how much weight to place on each opinion. This is especially difficult when the advisory opinions contradict each other or are at odds with the decision maker's own initial opinion. Two central concepts in this work are *egocentric judgment* and *satisficing*. We review their roles in advice taking.

Egocentric judgment. Self-centered judgments are common in social settings (e.g., Dunning & Hayes, 1996; Chambers, & Windschitl, 2004). Our previous findings suggest that people tend to be *egocentric* in revising their opinions. In particular, they tend to discount advice and favor their own opinion (Yaniv & Kleinberger, 2000; Yaniv, 2004a). This self/other effect has been observed in experiments using a "decide-advice-revise" paradigm where respondents form initial opinions and then revise them on the basis of one piece of advice. Consistent findings have been reported by others. In a cue-learning study by Harvey and Fischer (1997), respondents shifted their estimates about 20-30% towards the advisor's estimates. In another study by Lim and O'Connor (1995), judges weighted their own forecasts more heavily than advisory (statistical) forecasts. Sorkin et al. (2001) reported a related result based on a group signal-detection task. Finally, in a study involving the control of a simulated system, Gardner and Berry (1995, Experiment 1) report that participants ignored useful advice when it was given to them as an option.

Yaniv (2004b; Yaniv & Kleinberger, 2000) suggested the following explanation for this finding. From an *external* (objective) point of view, a respondent's initial opinion and the advisor's opinion are on equal footing. However, from the decision maker's *internal* (subjective) point of view, his or her own opinion and those of others are *not* on equal footing. Individuals are privy to their own thoughts, but not to those of others. They have less access to evidence supporting the advisor's view. The egocentric weighting of advice then results from the nature of the support the decision-maker can recruit for her own opinion versus the advice. Hence, other things being equal, decision-makers tend to discount advice.

A second egocentric effect is the *distance effect,* according to which individuals give less weight to advice the further it is from their initial opinion (Yaniv, 2004b). This finding is reminiscent of similar findings in the attitude-change literature. A basic tenet of all consistency theories of attitude change is that individuals seek to resolve discrepancies among their beliefs (Zimbardo & Leippe, 1991). Such theories predict that attitude change should decline with distance (Aronson, Turner, & Carlsmith, 1963; Sherif & Hovland, 1961). Bochner and Insko (1966) presented a persuasive message advocating that people get some specific number of hours of sleep per night (where the number ranged in various conditions from 8 to 0 hours). They found that as the advocated number of hours of sleep decreased (the discrepancy increased), the magnitude of attitude change decreased (assuming that change is expressed as a fraction of the distance between the initial attitude and the message). As the message became more extreme, people generated more counterarguments and tended to disparage the source.

This distance effect was seen also in studies of stereotype change (Kunda & Oleson, 1997), and conceptualized in terms of assimilation and contrast processes (Sherif & Hovland, 1961; Wegener, Petty, Detweiler-Bedell, & Jarvis, 2001). While a slightly deviant opinion can be

assimilated and thus cause a shift in one's attitude, a highly discrepant one accentuates the contrast; it has a reduced effect, since it falls outside the person's "latitude of acceptance" (Sherif & Hovland, 1961). Davis et al. (1997) also incorporated this idea into their social decision schemes. Their models describe how the opinions of groups (e.g., committees, juries) are aggregated during discussion to establish the group's consensual judgment. In their models, a discrepant opinion's impact on group decision quickly declines as the discrepancy increases.

Processing Opinions from Multiple Sources

The findings reviewed so far demonstrate the egocentric effects in the processing of a *single* piece of advice. Here we consider the egocentric processing of *multiple* pieces of advice. Investigating the processing of a number of pieces of advice is important for practical and substantive reasons. First, the number of opinions in real-life decisions varies. Patients facing nontrivial health problems often seek a second and even a third expert opinion. Editors typically solicit the opinions of two or three reviewers to make publication decisions; universities seek perhaps three to six recommendation letters prior to making job offers or making tenure decisions. Is it only that resource constraints (time, effort, money) limit the number of opinions searched prior to making decisions? Or does experience tell decision-makers that polling a few opinions may suffice, on average, to exhaust most of the information that could be possibly obtained? Perhaps both factors affect the number of opinions people seek. We explore systematically how the number of opinions presented to decision-makers (two to eight) affects how people use multiple sources (i.e., processing difficulty) and how much they benefit from them (i.e., marginal gains).

As the number of pieces of advice increases, so does the complexity of the integration. Task complexity generally leads people to rely more on heuristic shortcuts and to seek satisficing rather than optimal outcomes. For instance, when faced with a complex multidimensional choice (e.g., shopping) involving a large number of alternatives (e.g., brand names) and attributes that describe each alternative (e.g., price, quality, delivery), decision makers turn to heuristics that reduce the amount of information considered (Payne, 1974). In the present context, the need to integrate across conflicting opinions may lead people to employ satisficing rules and engage in data reduction. Finally, some important parameters in studies of conformity and majority influence on individuals are the size of the group and the size of the majority (e.g., Brown, 2000, Chap. 4). By varying here the numbers and configuration of advisory opinions we could explore the patterns of influence of advice.

The Benefit of Combining Advisory Opinions

How beneficial is the use of multiple advisory opinions? One might wonder whether non-expert advice is useful at all. In fact, advisors need not be smarter or more knowledgeable than the receiver of the advice to be valuable. For example, in a study involving estimation, participants reduced their initial error by about 20% by considering just one opinion of a fellow student drawn at random from a pool (Yaniv, 2004b).

There is ample evidence that averaging the opinions of several individuals increases accuracy. For example, a study of the accuracy of inflation forecasts found that averaging the opinions of several forecasters was superior to selecting the judgment of any of the individuals (Zarnowitz, 1984). While an individual forecaster might have outperformed the average on occasion, none did so consistently. Such results have been demonstrated in diverse domains, ranging from perceptual estimations of line lengths to business forecasts, and are an important motivation for research on combining estimates (Armstrong, 2001; Ashton & Ashton, 1985; Libby & Blashfield, 1978; Surowiecki, 2004; Winkler & Poses, 1993; Yaniv & Hogarth, 1993; Yaniv, 1997).

A number of formal models provide a theoretical basis for understanding when and how combining estimates improves accuracy (e.g., whether accuracy is measured in terms of mean

absolute error or judgment-criterion correlation). These include binary-choice models based on the Condorcet jury theorem (majority rules/ binary issues) and group signal-detection theory (Sorkin, Hayes, & West, 2001), models for combining subjective probabilities from multiple judges (Budescu, Rantilla, Yu, & Karelitz, 2003; Wallsten, Budescu, Erev, & Diederich, 1997), and models for combining point forecasts (Clemen, 1989; Hogarth, 1978). In the case of quantitative judgments, a brief outline can show how the use of advice might improve judgmental accuracy. According to the Thurstonian view, a subjective forecast about an objective event is the sum of three components: the "truth," a systematic bias, and random error. Statistical principles guarantee that forecasts formed by averaging several sources have lower variability (random error) than the individual opinions. The combined forecasts are expected to converge about the truth if the systematic bias is zero or fairly small (e.g., Einhorn, Hogarth, & Klempner, 1977).

Overview of the research

A key feature of the present research is its dual emphasis on descriptive and normative issues. First, we ask what policies or rules people use for revising their opinions when presented with multiple advice. In other words, how do advisory opinions influence people's final opinions? Second, we ask what policies or rules improve decision accuracy.

The experiments, which were conducted on a computer due to their interactive nature, shared the following general procedure. In the first phase, respondents were presented with questions and asked to state their estimates. In the second phase, they were presented with the same questions along with several advisory estimates drawn from a large pool of estimates made by other students. The respondents were then asked to provide their estimates once again. They were free to use the advisory opinions as they wished. In the first experiment, the number of advisory opinions presented varied from two to eight in different conditions and the advice was selected on-line at random by the computer from appropriate pools of estimates.

What rules might people use in revising their opinions? Conceivably, there is an infinite number of potential rules that decision-makers could use for aggregation. It is practically impossible to test or even enumerate any great number of them. We therefore focused on relatively simple heuristic revision rules. We assumed that individuals (a) seek to produce the most accurate estimates they can (adaptiveness), but (b) they rely on simple heuristic rules when dealing with conflicting opinions (satisficing), and (c) their own perspective plays an important role in the revision process (egocentrism).

We considered an array of revision rules, among them ones that assign equal weights to all opinions and others that discount some of the opinions. Some heuristics reduce dissonance through data reduction; they simplify the combination of opinions by trimming the set of opinions. Two types of trimming were considered. With egocentric trimming, the one (or two) opinions furthest from the decision maker's own opinion are dropped from consideration. With consensus-driven trimming, the opinions furthest from the group's consensus are dropped. Thus extremity of opinion is defined subjectively (egocentrically) in the former and objectively in the latter case.

The egocentric trimming rule was designed to evaluate the hypothesis that judges weight distant (incompatible) opinions egocentrically. The consensus trimming rule was needed as a comparison with egocentric trimming. More importantly, there is some evidence that consensus trimming improves accuracy above equal weighting (Yaniv, 1997). The discussion presents in some theoretical arguments justifying such trimming. Our descriptive analyses of how people revise their opinions are accompanied by a parallel normative data analysis designed to evaluate the adaptive value or success of each revision policy.

In the second experiment, the advisory opinions were not sampled from realistic pools, but were created artificially by design. The artificial profiles of near and far advice enabled us to conduct a series of linear regression analyses and compare weights (coefficients) for the two kinds of advice and also compute weight indices akin to those used in earlier studies (Yaniv &

Kleinberger, 2000). In sum, the experiments used a variety of data-analytical approaches to reach converging conclusions.

Experiment 1

This experiment investigated how people integrate their prior opinion with those of the advisors. The number of advisory opinions was two, four, or eight. The amount of advice was manipulated among participants. Two important notes are in order. First, our respondents received a bonus for making accurate judgments, so their decisions were consequential. We paid a bonus for each final estimate with a lower than average error, so it was in the respondents' interest to consider the advice carefully and make the best use of it, however they thought was appropriate. Second, a major advantage of the method of Experiment 1 is the representative sampling (Brunswik, 1955) of advice from pools of actual estimates made by other undergraduate students whom they might also have consulted in a natural situation.

Method

The experimental procedure was conducted individually on personal computers. Twenty-four questions about the dates of historical events (within the last 300 years) were presented sequentially on the computer display screen. As shown in Table 1, in the first phase respondents were shown one question at a time and asked to type in their best estimate for each one via the computer keyboard; in addition, they were asked to give lower and upper boundaries such that the true answer would be included between the limits with a probability of 0.95.

[Insert Table 1 about here]

After the first phase was over, the respondents were told that there would be a second phase in which they would be presented with the same set of questions again. Now, however, each question would be presented along with the respondent's own estimate (from the initial phase) and several advisory estimates made by others. The respondents would then be asked to give a second, possibly revised, estimate for the question. No online feedback was given on the accuracy of their own or the advisors' opinions (in particular, the correct answers were never shown). The respondents were told they would get a bonus at the end of the study, depending on their overall accuracy (see below).

In one condition (N = 55), respondents were given two advisory estimates on each trial. In the second condition (N = 61), they were given four opinions on each trial. In a third condition (N = 54), they were given eight opinions on each trial. The advisors' estimates were randomly drawn by the computer from a pool of 90 estimates collected in an earlier study in which respondents had been instructed merely to provide the best estimate for each question. For each question, new advisors were sampled at random. Thus the advisors varied from one question to the next, with labels such as #37, #81, and #15 used to indicate that the estimates came from different individuals in each trial. By adhering to representative sampling of estimates from pools of data, we insured that the dispersion of the estimates and their errors corresponded to those that might have been encountered in reality by our respondents when seeking answers to such questions among their peers -- undergraduate students.

The respondents were undergraduate students who participated either as part of their course requirements or for a flat fee of $4. They were all told that they would receive a bonus based on the accuracy of their estimates. In particular, they would receive $0.25 as a bonus for each estimate with a better than average accuracy score. Altogether they could collect up to $6 in bonus payments. Thus it was in their interest to pay attention to the advisory estimates and make the best use of them. The bonus was based on the final estimates (i.e., second phase).

Results

We carried out two sets of analyses. First, we evaluated the accuracy of the initial and revised estimates along with the accuracies of the estimates generated by each of the formal revision rules listed below. Second, we evaluated which revision rules best fit the participants' final estimates. In accord with our assumption that processing advice is both heuristic and egocentric, we included revision rules that were based on simple descriptive statistics and seemed easy to execute, as well as ones that gave greater weight to the respondent's own perspective. The rules differ systematically from each other, and thus permit comparisons aimed at unveiling which operations people might use.

We assessed the fit of the following revision rules: *Equal weighting (average)* is the simple average of all opinions (i.e., including one's own and the advice). *Discounting extremes (median)* is the median of all opinions. *Midrange* is the average of the highest and lowest opinions in the set. With *consensus-based trimming (type one)* the most extreme opinion is removed and the remaining opinions are simply averaged, while with *consensus-based trimming (type two)* the two most extreme (i.e., the highest and lowest) opinions are removed and the remaining ones are simply averaged. With the *egocentric trimming (type one)* the single advisory opinion that is furthest from the respondent's initial opinion is removed and the remaining opinions are averaged, while with the *egocentric trimming (type two)* the two furthest opinions from the respondent's initial opinion are removed, and the remaining opinions are simply averaged. We analyzed the fit of the various rules and used significance testing to assess the differences among them.

The benefit of multiple advice. Table 2 shows the accuracy of the intuitive estimates and the estimates obtained by the formal revision policies. The results for each advice condition are shown in a different row. The actual success of intuitive revision is seen in the accuracies of the *initial* and the *final estimates,* as shown in the leftmost two columns of Table 2. The respondents' estimates improved due to the advice. The magnitude of improvement (i.e., reduction in mean absolute error) was roughly 27% after getting two opinions, 28% after getting four opinions, and 33% after getting eight opinions. The gains were substantial, and increased monotonically as a function of the number of opinions, but the *marginal* gains diminished rapidly, as the number of opinions increased. The other columns in Table 2 show the accuracies of the revision rules. The best rules in each row are highlighted. Overall the median and consensus policies fared better.

[Insert Table 2 about here]

In subsequent analyses we compared the performance of the various policies using significance testing. Table 3 presents the sign test results for all pairwise comparisons between the accuracies of all the revision policies. The rules were listed in increasing order of accuracy (i.e., the mean absolute error decreases from left to right). Each entry indicates the number of times that a given *column* rule outperformed the corresponding *row* rule. As an illustration, Table 2 shows that the mean absolute error (in years) was reduced from 70.4 (initial-self estimate) to 51.7 (final-self estimate). Table 3 shows that final estimates were more accurate than the initial ones for 51 out of 55 participants, a significant difference, by the sign test, N^+=51 (out of N=55), N^- =4, N-ties =0, p < .01. Ties were generally rare and are indicated in the table whenever they occurred.

[Insert Table 3 about here]

Below we summarize the significant sign test results in a schematic graph. Policies are listed from left to right in increasing order of accuracy. Policies that were not significantly different from each other at p < .01 are joined by an underline. For example, the median and average were both better than all other policies, but they did not differ from each other in condition 1. In condition 2, both types of consensus-based trimming and the median policy did not differ from each other; but consensus trim-2 and the median were more accurate than the remaining policies. (This representation is not always easy to draw and depends on the "orderliness" of the significance of the pairwise comparisons.)

Condition 1: Self + 2 other opinions

Initial	Egocentric Trim 1	Midrange	Final	Consensus Trim 1	Average	Median

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Condition 2: Self + 4 other opinions

Initial	Midrange	Final	Egocentric Trim 2	Average	Egocentric Trim 1	Consensus Trim 1	Median	Consensus Trim 2

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Condition 3: Self + 8 other opinions

Initial	Midrange	Final	Average	Egocentric Trim 2	Egocentric Trim 1	Consensus Trim 2	Consensus Trim 1	Median

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The ordering of the rules was similar though not identical in all conditions. The data permit several conclusions. We find that the median rule is better than the average with five (self + 4) and nine (self + 8) opinions, and is as good as the average with three (self + 2) opinions. The two consensus heuristics performed well with five to nine opinions, but not with three opinions, presumably since such a small number of opinions does not permit useful removal. One conclusion is, briefly, that the operations that attenuate the influence of extreme opinions tend to increase accuracy. Overall the median (which effectively attenuates the influence of extremes) and the consensus heuristics (which literally removes opinions) performed best. A second conclusion is that individuals were able to benefit from the advice, but failed to extract all the information contained in it. Intuitive final estimates were less accurate than median and consensus trimming and averaging.

*The influence of advice.* What do people actually do? How do they open themselves to the influence of advice? Each revision rule represents a pattern of influence of multiple advice on respondents' final estimates. To assess this influence we calculated the fit of each rule with the final estimates, defined as the distance between the rule's prediction and the actual final estimate. Table 4 shows the global fit of each rule (i.e., the mean distance) in each advice condition (smaller numbers indicate better fit). Note first the rule labeled "initial self" – the strategy of staying with the initial estimate. This rule ignores all advice, thus technically representing the highest level of egocentrism. We found, in line with earlier findings, that judges adhered to their initial estimates in 38, 39, and 40% of the cases, in conditions 1-3, respectively. (They were correct less than 5% of the time in their initial estimates.) The two other egocentric rules ignore only the most distant (one or two) pieces of advice. The consensus rules, average, median, and midrange provide important benchmarks and are interesting because we have information about their accuracy.

[ Insert Table 4 about here ]

The two best fitting rules are highlighted in each row. In condition 1 (self +2), the median emerged as the best fitting heuristic, followed by egocentric trimming. With more opinions (self + 4, self +8), the best fitting heuristics involved egocentric removal of distant opinions. Of importance is the finding that the fit of egocentric trimming was better than that of objective trimming and equal weighting. The midrange was the worst fit. These results provide meaningful comparisons. The difference between the processes of egocentric trimming and averaging involves

just one operation, namely, the deletion of one or two opinions selectively. The difference between the processes of consensus trimming and egocentric trimming is the selection of the opinion(s) to be deleted prior to averaging. Finally, the midrange depends only on the extremes, in contrast with the median, which seeks the center and attenuates the effect of the extremes.

We conducted sign tests to compare the fits of the various rules. The results of all pairwise comparisons are shown in Table 5. For illustration, the comparison between the median and the midrange yielded results as follows: $N^+ = 51$ (out of N=55), namely, $N^- = 4$, $N^0=0$. (In general, ties are rare and were indicated when they occurred.) As can be seen, in condition 1 the median had a better fit than the other rules, except for egocentric trimming. The comparisons by and large support the conclusion that the egocentric heuristics provided better fits than the other schemes.

[ Insert Table 5 about here ]

Below we present a schematic summary of the pairwise comparisons shown in Table 5. The heuristics are shown in increasing order of fit from left to right, according to Table 4. Two heuristics were considered different if they differed at p<.01 level of significance; thus heuristics that did not differ at this level of significance were joined by an underline. This representation provides only an approximate summary of the results shown in Table 5. The main exception to the linear ordering of the heuristics occurred in condition 3, where the fits of the egocentric rules were not significantly better than those of the initial self (although the numbers shown in Table 4 suggest that the egocentric policies might have significantly better fit). This lack of significance does not, however, impair the overarching conclusion from these analyses. Either way the implication is that judges use advice egocentrically, either by egocentric trimming or by the most egocentric strategy of all – staying with one's initial opinion.

Condition 1:  Self + 2 other opinions

| Midrange | Initial Self | Average | Consensus Trim 1 | Egocentric Trim 1 | Median |
|---|---|---|---|---|---|
| | | _____ | ++++++++++++++++ | | |
| =================== | | | ------------------------- | | |

Condition 2:  Self + 4 other opinions

| Midrange | Initial self | Average | Consensus Trim 1 | Consensus Trim 2 | Median | Egocentric Trim 1 | Egocentric Trim 2 |
|---|---|---|---|---|---|---|---|
| | _____ | | | | | | |
| | ++++++ | | | ++++++ | | | |
| | | | | | ----------------------------------------------- | | |
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Condition 3:  Self + 8 other opinions

| Midrange | Initial self | Average | Consensus Trim 1 | Consensus Trim 2 | Median | Egocentric Trim 1 | Egocentric Trim 2 |
|---|---|---|---|---|---|---|---|
| | ++++++++++++++++++++++++ | | | | | | |
| | | ------------------------------ | | | | | |

*Conclusions.* A major advantage of *sampling* ecological advice, rather than creating the advice by design, is that it permits us to conduct descriptive and normative analyses – that is, to contrast the actual use of multiple advice and the strategies that appear to increase the benefits that could be reaped by using advice – all within the same experiment. Several findings are notable. First, individuals use advice egocentrically as the fits of the egocentric trimming rules suggest. Second, their accuracy gains are substantial. Third and more striking is the finding that the intuitively revised estimates are about as accurate as the worst (midrange) method (Table 2), and significantly worse than the egocentric trim strategies, the median, and the consensus trim

strategies. In the final discussion we will consider these findings and will present principled arguments for why consensus trimming boosts accuracy most.

## Experiment 2

This experiment further investigated the use of multiple advice. Unlike the previous experiment, which involved representative samples of advice (i.e., random draw from a pool), here the advice was constructed. The advice was created online for each participant, depending on the estimates he or she gave in the first phase. On each trial, two advisory opinions were created, one near and one far from the participant's initial opinion.

We investigated how near and far advice influence one's final opinion (accuracy was of less importance since the advice were manipulated rather than sampled). Using different data-analytical methods, we assessed, first, the utilization of each type of advice (near vs far), second, how participants' prior knowledge affects their utilization of advice, and third, the effects of the quality of the advice on it is used. The findings allow us to assess the revision rules and the theoretical explanations of egocentrism in opinion revision.

*Method*

*Procedure.* The procedure included two phases, as in Experiment 1. After producing initial estimates, respondents (N = 75) received the same questions again along with the advice and were instructed to provide their final estimates.

For each question two pieces of advice were generated online by the computer at the end of phase 1 (i.e., after the initial estimates were entered). The pieces of advice (near and far estimates) were a function of the participant's estimate in phase 1; they were generated by either adding or subtracting certain factors to or from the initial estimates. The factors for a given question depended on the actual spread of the pool of answers estimating that question. For each question, we calculated the inter-quartile range (IQR) of a pool of 70 estimates (collected in earlier studies). The factors added to (or subtracted from) the initial self opinion were a function of IQR; specifically, for the near advice the factor was 0.3*IQR and for the far advice, 0.9*IQR. Using IQR in creating the factors lent credibility to the advisory opinions by ensuring that they were well within the natural spread of estimates for each question. In addition, the different questions had different spreads of answers (IQR) and hence different factors for each question.

There were four conditions, each involving a different configuration of the near and far advice vis-à-vis the truth. In condition 1, both pieces of advice always pointed *away from the truth* (technically, when the initial opinion was below the truth the relevant factor was subtracted from it, and when the initial opinion was above the truth the factor was added to it). In condition 2, both pieces of advice pointed *towards the truth* (i.e., when the initial opinion was below the truth the relevant factor was added to it, and when the initial opinion was above the truth the factor was subtracted). In condition 3, the far advice pointed away from the truth, while the near advice pointed towards the truth. In condition 4, the far advice pointed towards the truth, while the near advice pointed away from the truth.

There were a total of 28 trials. We used the same 24 questions as in Experiment 1, plus four new ones. Seven questions were randomly assigned to each of the four advice configurations, and trials in all four conditions were presented in a new random order for each participant. Thus advice configuration was a within-subject factor with four levels. The instructions were the same as in the Experiment 1. Nothing was said to the participants about how the estimates were created. The participants were told that they could earn up to $7 as a bonus for accuracy. Hence it was in their interest to consider their answers carefully and make the best use of the advice provided.

*Results*

      We analyzed the rules that participants used in revising their prior opinions as a function of participants' knowledge. Prior to the analyses participants were divided into high- and low-knowledge groups according to the accuracy of their estimates in the *first* phase. Using the median-split method, high-knowledge participants had mean absolute errors below the median and the low-knowledge ones had mean errors above the median.

      The first set of analyses involved three variants of linear regression, a method that has been commonly used in analyses of implicit weighting policies in multiple-cue judgment tasks and "lens" models (e.g., Einhorn, 1972). With this method, the final estimates are regressed on three predictors: initial estimate, near advice, and far advice, with the coefficients representing the weights assigned to each opinion.

      The estimation of the regression coefficients tends to be unstable if the predictors are intercorrelated (a common concern in judgment analysis). Therefore we report the results based on three alternative approaches. First, we performed a stepwise procedure for *each* participant separately, focusing only on the first predictor selected in each regression. Second, we performed a simultaneous regression (entering all variables at once) for *each* participant, looking at systematic differences among the coefficients obtained *across* all 75 individual regressions. Third, we report the utilization indices as recommended in the literature on judgment analysis (Cooksey, 1996, pp. 165-167) to circumvent the problem of intercorrelation.

      *Stepwise regression.* For each participant, the final estimates were regressed on three variables (initial estimate, near advice, and far advice) using the SPSS forward stepwise procedure (F-to-enter significant at p = .05). We considered here only *which* predictor was selected *first*. The first predictor selected was the initial estimate (the self) in 71% of the regressions (53 of 75), the near advice in 28%, and the far advice in 1%. Similar results were seen in both knowledge groups. In the high-knowledge group (n= 38), the first predictor selected was the *self* in 71% of the regressions (27 of 38), and the *near advice* in 29%. In the low-knowledge group (n= 37), the first predictor was the *self* was in 65% of the regressions, *near advice* in 32%, and *far advice* in 3%. By limiting our frequency statistics to the first predictor selected only (thereby ignoring the information on the remaining predictors), we bypass the intercorrelation issue. This conservative approach suggests that, overall, the self was the best predictor of the final estimates (followed by the near advice).

      *Simultaneous regression.* For each participant, the final estimates were regressed on three predictors: initial estimate, near advice, and far advice. Three predictor coefficients were obtained for each participant; their averages are shown in Table 6 (left). The high-knowledge participants placed the largest weight on the self, lower weight on the near advice, and the lowest weight on the far advice. The low-knowledge participants placed roughly the same weights on the self and near advice, and lower weight on the far advice.

[ Insert Table 6 about here ]

      The coefficients were compared statistically within groups by sign tests. For the high-knowledge group (N = 38), there was a significant difference between self and near advice, $N^+$=26 out of 38 (no ties), p<.05, and between near and far advice, $N^+$=31 out of 38 (no ties) p<.001. For the low-knowledge group (N = 37), there was a significant difference only between near and far advice, $N^+$=28 out of 37 (no ties), p<.005. Finally, between-group comparisons showed that the low-knowledge group paid more attention to the far advice than did the high-knowledge group (Mann-Whitney test, z = 4.53, p<.001). In sum, the simultaneous regression is generally susceptible to problems due to multicollinearity (intercorrelations among predictors), in that the estimation of the regression coefficients tends to be highly variable, and hence, less stable. Despite this variability, the obtained pattern was consistent across the sample of 75 judges, and also consistent with the stepwise results, suggesting preference for the self and the near advice.

*Utilization indices.* Cooksey (1996, pp. 165-167) recommends the use of "utilization indices" when the predictors are intercorrelated. The utilization of the $i$th predictor is its unique contribution – what one loses in predictive power by deleting it from the regression equation. It is computed as the difference between the full model (including three predictors here) and the reduced model including all but the $i$th predictor. In other words, it is the squared semi-partial correlation of the $i$th predictor with the criterion. The utilization indices were computed for each participant and then averaged (Table 6, right).

The utilization indices were compared within and between the knowledge groups. The high-knowledge group had utilization indices (self > near advice > far advice) that were the same as those of the regression coefficients; the three pairwise comparison were significant at p<.05, by the one-tailed sign test (self vs near, near vs far, self vs far), $N^+=25$ out of 38 ($N^+$ was the same in all comparisons, no ties). The low-knowledge group utilized the far advice more than the near advice, $N^+=29$ out of 37 (no ties), p<.05, but the self vs far contrast was not significant, $N^+=29$, p>.5. Finally, Mann-Whitney comparisons *between* the knowledge groups showed that the low-knowledge group utilized the far advice more than the high-knowledge group ($z = 3.11$, p<.05) while the high-knowledge group utilized the self more than the low-knowledge group ($z = 2.99$, p<.05). In sum, the utilization analyses suggest that the low-knowledge group utilized the far advice more than was revealed by the previous analyses. The various regression approaches generally agreed, but not always. Cooksey (1996) notes that differences between the utilization indices and the regression coefficients are to be expected if the predictors are intercorrelated.

*The weight index.* The second analysis was meant to complement the regressions. We created an index of the location of the final estimate relative to the initial opinion and the advice. We defined the "weight index" = $|f - aa| / |i - aa|$ where i, f, and aa stand for initial self opinion, final, and average advice, respectively. With this index, the final estimate is represented as a weighted combination of the *initial self estimate* and the *average of the two pieces of advice.* This weight measure, which is akin to those used earlier (Yaniv & Kleinberger, 2000; Yaniv, 2004b), enables us to compare behavior across the four experimental conditions.

As an illustration, suppose the initial estimate is 1850 and the average advice is 1880. The weight index takes a value of 1.0 if, in making the final estimate, the judge adheres completely to her initial estimate (1850); and 0 if the judge shifts completely to the average advice (1880). Intermediate weights between 0 and 1.0 indicate that the final estimate was in the range between the initial self and the average advice (1850 to 1880). A index value lower than 0 indicates that the judge shifted even beyond the average advice (e.g., above 1880), while values greater than 1.0 indicate that the judge shifted beyond the self (e.g., below 1850). Equal weighting involves placing weights of one-third on the self and two-thirds on the average advice.

The mean weight index – which can be interpreted as the participant's weight on her own initial opinion – is shown as a function of participants' knowledge in Table 7. A weight index of one-third (0.33) would be obtained if participants relied on their own opinion no more but also no less than they relied on advice. The actual mean weight (0.71) was significantly higher than 0.33, $t_{74} = 14.6$, p < .001, suggesting that participants relied more on their own opinion than on the advice. (This result is consistent with earlier ones with just one advisory opinion; Yaniv & Kleinberger, 2000). High-knowledge participants had higher weight indices than low-knowledge ones (0.83 vs 0.60), $t_{73} = 5.14$, p < .001. Thus the high-knowledge participants relied less on the (average) advice.

[ Insert Table 7 about here ]

The mean weight index, shown in Table 8 as a function of advice configuration, suggest that participants had valid intuitions about the quality of the advice. Consider the two leftmost conditions. Participants correctly shifted more towards the average advice in condition 2 (*both towards)* than in condition 1 (*both away)* (0.54 vs 0.63), $t_{74} = 2.53$, p < .05. Similarly, a comparison between the two rightmost conditions shows that the participants placed more weight

on the average advice when it pointed in the direction of the truth (*far towards the truth*) than when it pointed away from the truth (*near towards truth*) (0.67 vs 1.01), $t_{74} = 3.71$, p < .05.

[ Insert Table 8 about here ]

*Accuracy gains and losses due to advice.* Unlike Experiment 1, accuracy was not a focal issue here since the advice was manipulated. As might be expected, the accuracy of the final estimates improved or declined depending on the type of advice presented. We observed a 15% accuracy gain in condition 2 (*both towards*), and a 20% accuracy loss in condition 1 (*both away*). In the mixed conditions 3 and 4, the changes were minute: a 3% gain in condition 3 (*far towards the truth*) and a 1% loss in condition 4 (*near towards truth*). One-way analysis of variance on the gain/loss variable (absolute error of initial estimate minus absolute error of final estimate) found significant differences among the four conditions, $F_{3, 296} = 76.9$, p < .05. Specifically, conditions 1 and 2 differed from each other (Tuckey-HSD, p < .05); conditions 3 and 4 did not differ form each other, but they each differed from both condition 1 and condition 2.

Clearly, good advice helps decision makers, while poor advice leads them astray. Gains are a function of the quality of the advice as much as of the revision rules that one uses. These findings seem to underscore the importance of representative sampling of advice in assessing accuracy gains.

*Conclusions.* According to the stepwise- and simultaneous-regression results, all participants used egocentric revision rules. While the utilization analyses of the high-knowledge group exhibited a similar pattern, the utilization indices for *far advice* and *self* did not differ significantly in the low-knowledge group. Between-group comparisons showed that low-knowledge participants utilized the far advice more than high-knowledge participants, but they utilized the *self* less than high-knowledge participants. Overall, these results indicate that participants' policies were sensitive to the *quality of their own knowledge*. The analyses based on the weight index suggest that participants were sensitive also to the *quality of the (average) advice*, giving it more weight in the conditions where it pointed towards, rather than away from, the truth. In sum, despite their general egocentric approach, participants were not oblivious to the quality of others' and their own opinions.

## General Discussion

Our experiments considered the process and consequences of using multiple advice. Specifically we investigated, first, how decision-makers integrate opinions from multiple sources of advice (process), and second, whether and how much decision-makers gain from using such advice (consequences).

*The Benefit of Advice: Human vs Formal Revision Rules*

*Accuracy gains achieved by the judges.* Exposure to a number of advisory opinions (either two, four, or eight in Experiment 1) helped participants improve their intuitive estimates dramatically – their accuracy gains were 27%, 28%, and 33% in the three conditions, respectively. But the marginal gains diminished quickly, since two opinions were enough to yield most of what could be gained by considering a larger sample of opinions. The seemingly puzzling result that additional opinions do not contribute much to accuracy has been observed in some earlier studies (e.g., Ashton & Ashton, 1985; Libby & Blashfield, 1978) and discussed theoretically (e.g., Hogarth, 1978; Wallsten et al., 1997; Johnson, Budescu, & Wallsten, 2001).

What could explain this phenomenon? Briefly, the accuracy gains accrued from aggregation are optimal if the advisors are independent. Gains of appreciable size may also obtain where there are low or moderate positive correlations among experts (Johnson et al., 2001). However, the greater the *dependence* among the advisors, the lower the marginal gains of adding any one of them to the total. In many realistic situations – and our experiment is not an exception – some level of (statistical) dependence among advisors is to be expected. For instance, advisors may rely on

similar information sources or have similar backgrounds (Soll, 1999); moreover, in some real-life situations they may even consult one another, in which case additional advice is merely "more of the same." Along the same lines, Sunstein (2003, chap. 9) brings realistic data from a study on dependence among appellate judges in making the case for "why society needs dissent."

Apart from dependence, the presence of *systematic bias* further curtails the potential benefits of adding opinions. The greater the bias (e.g., systematic over- or under-estimation of the true value), the lower the gains from combining opinions. These structural considerations explain the fact that asymptotic accuracy levels are reached with very few advisory opinions.

*Shortcomings of human revision.* Although the potential accuracy gains from advice are limited in principle, individuals failed to exhaust even those that were possible. Normative analyses revealed that most formal revision policies were as good or better than intuitive revision. The phenomenon that simple strategies (e.g., equal weighting) outperform intuitive judgments is conceptually analogous to classic findings from the study of linear (lens) models of judgment. Simple weighting policies that assign weights to the cues (predictors) consistently yield predictions that are more accurate than those produced by individual judges who have access to the same cues (Dawes, 1979; Einhorn, 1972; Einhorn & Hogarth, 1975).

The predominant explanation for this finding in the judgment literature is that the *inconsistent* application of a judge's weighting policy leads to inferior intuitive judgments. First, judges make random errors in applying their own judgment policy. Second, judges switch strategies or consider intricate interactions among the cues, rather than applying a consistent weighting of the cues. The net effect of both tendencies is lower performance than with weighting policies that are consistently applied (Camerer & Johnson, 1991). The lesson from the judgment analysis literature is not negated here – our decision-makers were outperformed by equal weighting and trimming policies. Harvey, Harries, and Fischer (2000) also reached a similar conclusion. In their study participants estimated the monthly sales figures for an unknown product on the basis of forecasts made by four advisors. Accuracy feedback was also presented. Harvey et al. report that participants' global estimates were less accurate than a weighted average of the input advice.

*When might ignoring advice be beneficial?* We obtained the intriguing finding that *the removal of extreme opinions* outperformed simple averaging. Clearly, an outlying opinion is not necessarily wrong. However, under certain conditions dissenting opinions are likely to be wrong, which would justify removing them (Yaniv, 1997; Harries et al., 2004). Assume a bell-shaped, thick-tailed distribution of opinions – that is, the prevalence of outlier opinions is larger than would be expected under the standard bell-shaped (normal) distribution. Under such conditions (assuming zero or small bias), an extreme opinion in a sample is particularly likely to be wrong. Given an underlying symmetric distribution with relatively thick tails, a *trimmed sample mean* is to be preferred to the raw sample mean as an estimator of the central tendency of the distribution (e.g., DeGroot, 1986, pp. 564-569; Wilcox, 1992; see also Streiner, 2000). Indeed, the distributions of human responses frequently have one or two thick tails, as Micceri (1989) has found. In sum, such statistical conditions warrant consensus-based trimming of extreme opinions.

To see the relevance of these arguments to small samples (e.g., of five or nine opinions), consider a *hypothetical binary* situation where 90% of the advisors' estimates are classified as near the true value, and the remaining 10% are far from the truth. In this scenario, far opinions impair accuracy. What are the chances that a far opinion would be included in a small sample of opinions? If a sample of five opinions is drawn at random from this population, then the chances of it including at least one far opinion is 35%. If the distribution is composed of 80% near opinions and 20% far opinions, then the chances of encountering at least one far opinion in a sample of five rises to almost 60%. The high likelihood of including far opinions in small samples (assuming thick tails) may explain why consensus trimming is such a powerful heuristic.

In sum, under some conditions removing dissenting opinions might increase accuracy. Removing opinions that are distant from the *self*, rather than from the *consensus*, raises different

issues, however. In principle, by ignoring discrepant opinions that challenge them, people reduce their ability to learn and update their opinions. It has been shown how selective incorporation of evidence leads to perseverance of attitudes (Lord, Ross, & Lepper, 1979). In the same manner, egocentrically trimming discrepant opinions results in conservative revision of opinions. Our normative results indeed show that egocentric trimming is inferior to consensus trimming.

*The Influence of Advice: Human Revision Rules*

We assessed the fit of simple heuristic rules in Experiment 1 to uncover some of the mental operations that people use in processing samples of opinions. This is important since, as we suggested above, the benefits of using advice depend on *how* it is processed. While we did not locate a single rule that characterizes universal behavior on every trial (in fact, there might not be any), our data do provide evidence regarding people's approaches to the task. First, the revision process was highly egocentric, as several types of evidence indicate. In both experiments the participants were correct less than 5% of the time in their initial estimates, yet they adhered to them in roughly 35-40% of the trials, changing their opinions in only the remaining 60-65%. Then, among the revision heuristics considered in Experiment 1, egocentric trimming provided the best approximation of the influence of 4 or 8 pieces of advice on participants' final estimates.

While Experiment 1 used representative (ecological) samples of advice, namely, opinions that were randomly drawn from pools of estimates, Experiment 2 used artificial (near and far) advice that was created systematically as a function of the participant's initial estimate. Several analyses of suggest that decision-makers' revision policy here was egocentric, giving greater weight to confirming (i.e., near) advice than to disconfirming (i.e., distant) advice; at the same time their revision policy was also sensitive to how much they knew to begin with. In Experiment 2 we analyzed separately high- and low knowledge participants. The high-knowledge participants clearly placed more weight on their own opinion and on near advice than on far advice (stepwise and simultaneous regressions; utilization indices). The low-knowledge participants considered the advice more than did the high-knowledge participants (regression); the utilization indices showed that they generally placed more weight on the far advice than on their own opinion and on near advice. Considering all the evidence, it appears that participants were sensitive to their own knowledge showing greater utilization of the advice when they know actually less.

Our research adds to a body of results on the use of others' opinions, most of which involves *combining* opinions rather than *revision* of one's own prior opinion. In a recent study, participants combined a set of forecasts of the next day's temperature for each of a series of places in the UK (Harries et al., 2004). The actual places were not identified by name so the participants could not have any specific prior opinion. It was found that participants relied heavily on consensus trimming (egocentric trimming was not an available strategy, to be sure).

Budescu et al. (2003) suggested that judges aggregate opinions by a weighted average rule rather than a median rule. In their studies the opinions to be combined were bounded (probability estimates). Two important aspects distinguish our setup from theirs. First, in our setup the distribution of estimates was unbounded and included numerous extreme values, thereby increasing the appropriateness of trimming operations. Secondly, in their paradigm participants *combined* others' opinions, whereas in ours participants *revised* their own initial opinions. Both of these aspects seem likely to increase the tendency to discount or ignore distant opinions.

The studies reviewed above show that both the revision (or mere combination) rules and the ecology (i.e., the characteristics of the opinions) determine both what people *do* and what they *achieve* in revising (or combining) opinions. A practically unbounded scale of response, such as the one we used here, has the potential of revealing large disagreements among naïve advisors. Will the trimming results generalize to expert advice? This seems to depend in part on whether experts exhibit less variance of opinion. While we leave this as an open question for future research, we offer some observations that experts may disagree. It is not uncommon for expert reviewers to present widely divergent views on an article submitted for publication. Another vivid

real-life example of expert disagreement appears in a recent *Nature* report entitled "Rival monsoon forecasts are banned" (Jayaraman, 2005).  Since the Indian economy relies heavily on farming, accurate weather forecasts are critical.  A ban on internet posting of "dramatically different" meteorological forecasts was called for, according to the Indian government, "to stop the public being confused by conflicting forecasts" (p. 161).  The occurrence of conflict, even in forecasts produced by experts, suggests that trimming strategies may be applicable in combining expert judgments as well.

*An account of egocentric judgment.*

How are we to explain the egocentrism in processing advice sets?  First, selectively ignoring opinions that are inconsistent with one's own opinion clearly simplifies cognitive processing (Harries et al., 2004; Yaniv, 1997).  A second and a more profound rationale is based on the assumption that people take a subjectivist approach to belief updating (e.g., Hogarth & Einhorn, 1992).  Thus they weight a new opinion as a function of their confidence in their *own* opinion.  Under this assumption egocentric discounting results from judges' differential access to the evidence underlying each opinion.  People naturally have more access to the reasons underlying their personal opinion than to those underlying the advisors' opinions.  Since their own evidence is more consistent with near advice than with far advice, they weight the former more heavily.  This explanation is akin to other theories of attitude change (Lord et al., 1979) which posit assimilation and contrast processes; near advice is presumably assimilated, whereas far advice accentuates the contrast; advice that falls outside the "latitude of acceptance" is discredited and hence ignored (Sherif & Hovland, 1961).

This contrast between internally generated information and external sources has been suggested in previous work as well.  Kohler (1994) suggested that individuals assess the truth of a focal hypothesis differently, depending on whether they themselves selected it (in a binary choice task) or the selection was made by someone else.  He found that individuals expressed more confidence in the pre-selected hypothesis (see also the "cueing effect" in Ronis & Yates, 1987).  Kohler suggests that self-generation boosts the retrieval of elaborate evidence (i.e., pros and cons), which leads individuals to express more caution.  These studies, however, did not involve the integration of own opinions and advice.

In a study by Sniezek and Buckley (1995) decision-makers received the opinions (answers to binary-choice questions) of two advisors in one of three conditions.  In the first, the decision-makers formed their prior opinions on the questions *before* getting the advice (i.e., a decide-advice-revise paradigm); in the second, they received the questions *along* with the advice; and in the third, they merely formed their opinions on the basis of advice alone, without knowing what the questions were.  Interestingly, the first condition yielded the highest accuracy, suggesting the importance of generating one's own position prior to getting advice.  Decision-makers in the first condition also were less likely to change their opinions based on the advice than those who did not form a prior opinion (i.e., the second condition).  These findings suggest that the possession of an egocentric perspective is beneficial (compared to not having one), but it also reduces one's willingness to change one's mind.

Finally, disagreement among the advisors may lead judges to ignore all advisors' opinions alike, thereby exacerbating egocentrism.  Studies of multiple-cue judgments have shown that judges who are presented with inconsistent cues tend to place less weight on *all* of them (Slovic, 1966; Sniezek & Buckley, 1995).  The public arena suggests similar observations.  An open debate among experts on a given topic – say, about health risks associated with certain types of food, diet, or a new hazardous technology – decreases the public's trust in all expert opinions (Slovic, 1993).  As trust in others dwindles, one's own opinion remains as a salient default, leading to an egocentric revision process.

*Cognitive vs motivational determinants of egocentrism.*  It is often the case that human judgments are multi-determined, so that several factors conjoin to yield the same effect.  In our

experimental tasks, cognitive and motivational factors coincide in their predictions. We outlined earlier the cognitive explanation for the egocentric updating of opinions. We now consider the merits of two motivational accounts of the findings.

One motivational explanation posits a self-serving bias, such as the "above-average effect," as the root of discounting others' views. The above-average effect pervades interpersonal comparisons, in that, for example, people believe that they have smaller chances of experiencing negative life events, such as road accidents or strokes, than others, or that they rank higher than others on various abilities and attributes, such as driving ability and social skills (Chambers, & Windschitl, 2004). Interestingly, though, researcher have presented compelling evidence that *cognitive* mechanisms (chiefly, people's egocentric focus in comparative judgments) play a major role in generating the above-average and optimism effects (Chambers, & Windschitl, 2004; Kruger (1999), phenomena that had been considered the domain of motivational explanations.

We suggest that a self-serving bias by itself does not readily explain the results of Experiment 2, namely participants' sensitivity to *their own knowledge* as shown by the regression (as well as utilization) coefficients and their sensitivity to the *quality of the advice* as shown by the comparisons of the weight indices (see also Yaniv & Kleinberger, 2000). To explain these effects one would need to extend the motivational bias by including cognitive components, which are part and parcel of the cognitive explanation.

Another prominent alternative account is people's commitment to their past decisions. The motivation to maintain commitment to a prior course of action plays a role in decision making in general (Cialdini, 1993, chap. 3). The antecedents of commitment are often the high cost of being inconsistent, the need to justify decisions to others, having to admit past mistakes and the wish to save face (e.g., Brockner, Rubin, & Lang, 1981). It seems though that these antecedents were largely absent in the present studies. Our participants made their judgments in a private setting (by entering responses into a computer file) and were not asked to justify their estimates. Moreover, they received bonuses for the accuracy of their final estimates – incentives that should promote both the willingness and the rationale to revise prior opinions as needed. Indeed, the less knowledgeable participants changed their opinions (gave greater weight to advice) more than the more knowledgeable ones (Experiment 2). The cognitive account readily explains such findings, whereas the prior commitment account does not readily explain them, without further cognitive assumptions.

Notwithstanding our arguments in favor of a cognitive explanation, we cannot rule out the possibility that prior commitment also contributed to egocentric discounting in our studies. Some residual effects due to the need for consistency might be ever present, even under conditions that reduce commitment pressures, as in the present studies. We suggest though that, regardless of the position that one takes on the role of commitment and the sufficiency of the cognitive explanation, the *prescriptive* implications of this research remain, in our view, largely intact.

*Implications*

The present findings have important prescriptive implications. Clearly people extract useful information from advice – their final self-estimates are more accurate than the initial ones. The presumed advantage of advice – as a source of potentially disconfirming information – has been proven correct. It is important to reiterate that to be helpful advice does not need to arrive from more knowledgeable sources – just (fully or semi) independent ones! Schotter (2003) also observes that "most of the time we make decisions relying only on the rather uninformed word-of-mouth advice we get from our friends or neighbors." He calls this naïve advice. Schotter's game-theoretical experiments, which involved naïve rather than expert advice, also suggest that participants behave in a more rational manner when they make decisions under the influence of advice (Schotter, 2003).

Notwithstanding the benefit of naïve advice, people discount or ignore some of the advice in forming their final judgments. In that sense they limit their opportunities to benefit from disconfirming evidence. Indeed, consistent application of almost any of the rules that we have examined (e.g., equal weight, median, consensus trim) outperforms intuitive judges, suggesting the merits of consistency. Finally, a general prescriptive implication is that judicious removal of extreme opinions (using consensus-based trimming or the median) yields the most accurate global judgments.

Aside from the prescriptions for better utilization of advice, these results also have a theoretical message. A fundamental issue in the literature in recent decades has been the rationality of human behavior, in light of the research showing flaws in intuitive judgment and decision making. A pervasive impediment to human judgment appears to be the difficulty of generating alternatives to one's current thoughts. Framing effects, anchoring, and confirmation bias all arise when people fail to generate relevant alternatives. Seeking and utilizing advice can be viewed as an adaptive *social decision-support system* that helps individuals encounter new alternatives. Advice, be it a new anchor, a different frame, or a piece of disconfirming information, can trigger beneficial thought processes.

*Reservations and limitations.* Our study investigated only a small set of possible revision rules out of a large number of possibilities. The rules we evaluated here were static and global rather than dynamic and contingent; they were applied universally, regardless of context, and had no "memory" for past successes or failures. Our results are therefore only an approximation of the underlying processing of opinions. Might dynamically complex rules with contingencies lead to deeper insights? We cannot rule out this possibility, though it is also plausible that complex rules would be more costly in terms of added parameters, as well as difficult to interpret. Research on judgment analysis has pointed out that simple models of judgment (of the sort used here) are rarely surpassed by more complex ones (Einhorn & Hogarth, 1975). Finally, our goal was to gain insights into the basic mental operations involved in revising opinions. The use of simple strategies seems to fit this task.

Our final comment concerns the limited scope of the advice studied here. We only considered *quantitative* advice. Whereas numerical forecasts are important in real life, everyday decision-making also involves *qualitative* advice. Moreover, advice is sometimes presented along with supporting arguments. Future research should focus on the integration of other advice formats, such as probabilities (Yates, Price, Lee, & Ramirez, 1996), preferences, and advice supported by arguments (Jonas & Frey, 2003). While we anticipate that the basic revision mechanisms found here will also be relevant to other sorts of advice, we believe that new research will shed more light on advice-based decision processes.

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Table 1

*Sample Question and Outline of the General Procedure*

_____

Phase 1 (series of 24 questions):

In what year was the Suez Canal first opened for use?
Your best estimate _____ (low estimate _____ high estimate___ )


Phase 2 (same 24 questions repeated):

In what year was the Suez Canal first opened for use?

Your previous best estimate was  _1905_

The best estimate of advisor #33 was  _1830_

The best estimate of advisor #16 was  _1830_

Your final best estimate  _____

_____

Table 2

*Analysis of the Benefit of Advice: Accuracy (Mean Absolute Error) of Intuitive Judgments and Revision Rules*

| Number of Opinions | Initial | Final | Median | Mean | Consensus trim 1 | Consensus trim 2 | Egocentric trim 1 | Egocentric trim 2 | Midrange |
|---|---|---|---|---|---|---|---|---|---|
| Self +2 | 70.4 | 51.7 | **<u>46.1</u>** | **46.9** | 48.9 | -- | 55.3 | -- | 50.1 |
| Self +4 | 69.6 | 50.2 | **41.1** | 42.8 | 41.2 | **<u>40.4</u>** | 44.6 | 50.0 | 50.6 |
| Self +8 | 71.5 | 47.8 | **<u>36.9</u>** | 40.7 | **38.0** | 38.8 | 40.2 | 41.3 | 52.0 |

Note: The numbers are the mean absolute errors resulting from estimating the truth according to each of the schemes.

The best fit appears underlined and bold; the second best appears in bold.

Table 3

*The Accuracy Gains of Intuitive Revision and the Various Revision Rules:  Sign Test Pairwise Comparisons (entries show the number of times the column rule outperforms the row rule; * 5% ;  ** 1%)*

**Condition 1:  3 opinions (self  2)**          N =55

| | Median | Average | Consensus-based trim 1 | Midrange | Self final | Egocentric trim 1 |
|---|---|---|---|---|---|---|
| Self initial | 41  ** | 47  ** | 46  ** | 47  ** | 51  ** | 46  ** |
| Egocentric trim 1 | 44  ** | 44  ** | 38  ** | 41  ** | 39  ** | |
| Self final | 40  ** | 38  ** | 30 | 30 | | |
| Midrange | 41  ** | 51  ** | 36  * | | | |
| Consensus trim 1 | 45  ** | 30 | | | | |
| Average | 34  1= | | | | | |

**Condition 2:  5 opinions (self + 4)**          N =61

| | Consensus-based trim 2 | Median | Consensus-based trim 1 | Egocentric trim 1 | Average | Final | Egocentric trim 2 | Midrange |
|---|---|---|---|---|---|---|---|---|
| Initial | 54  ** | 53  ** | 52  ** | 58  ** | 53  ** | 53  ** | 58  ** | 47  ** |
| Midrange | 58  ** | 55  ** | 55  ** | 51  ** | 59  ** | 35 | 32 | |
| Egocentric trim 2 | 46  ** | 47  ** | 46  ** | 52  ** | 44  ** | 34 | | |
| Final | 47  ** | 47  ** | 47  ** | 45  ** | 44  ** | | | |
| Average | 47  ** | 41  1= ** | 38 | 39  * | | | | |
| Egocentric trim 1 | 46  ** | 46  ** | 39  * | | | | | |
| Consensus trim 1 | 38 | 32 | | | | | | |
| Median | 35  1= | | | | | | | |

Table 3 (continued)

*The Accuracy Gains of Intuitive Revision and the Various Revision Rules:  Sign Test Pairwise Comparisons (entries show the number of times the column rule outperforms the row rule; * 5% ;  ** 1%)*

**Condition 3:  9 opinions (self + 8)**          N =54

| | Median | Consensus-based trim 1 | Consensus-based trim 2 | Egocentric trim 1 | Egocentric trim 2 | Average | Self final | Midrange |
|---|---|---|---|---|---|---|---|---|
| Self initial | 51 ** | 50 ** | 49 ** | 51 ** | 53 ** | 48 ** | 53 ** | 40 * |
| Midrange | 52 ** | 53 ** | 54 ** | 53 ** | 52 ** | 54 ** | 34 | |
| Self final | 42 ** | 41 ** | 40 ** | 42 * | 43 ** | 36 * | | |
| Average | 45 ** | 44 ** | 50 ** | 32 | 30 | | | |
| Egocentric trim 2 | 40 ** | 37 ** | 34 | 35 * | | | | |
| Egocentric trim 1 | 44 ** | 38 ** | 32 | | | | | |
| Consensus trim 2 | 40 ** | 37 ** | | | | | | |
| Consensus trim 1 | 34 | | | | | | | |

Table 4

*Which Rule Best Explains the Influence of Advice?  Fits of Revision Rules (mean absolute deviation)*

| Number of Opinions | Stay w/ Initial | Final | Median | Mean | Consensus Trim 1 | Consensus Trim 2 | Egocentric Trim 1 | Egocentric Trim 2 | Midrange |
|---|---|---|---|---|---|---|---|---|---|
| Self +2 | 36.2 | -- | **23.9** | 31.5 | 29.5 | -- | **27.9** | -- | 36.5 |
| Self +4 | 38.3 | -- | 29.3 | 34.2 | 32.8 | 31.1 | **27.9** | **27.5** | 42.6 |
| Self +8 | 38.2 | -- | 33.0 | 35.5 | 34.8 | 34.6 | **31.1** | **29.0** | 45.6 |

Note: The numbers are the mean absolute deviations indicating the fit of each rule to the final opinion.  Lower numbers indicate better fit of the rule.

The best fit appears underlined and bold; the second best appears in bold.

Table 5

*Which Rule Best Explains the Influence of Advice?  Pairwise Comparisons (Sign Tests) of rules (entries show the*

*number of times the column rule outperforms the row rule; * 5% ;  ** 1%)*


**Condition 1:  3 opinions (self + 2)**          N =55

|  | Median | Egocentric trim 1 | Consensus-based trim 1 | Average | Self initial |
|---|---|---|---|---|---|
| Midrange | 51 ** | 42 ** | 41 ** | 54 ** | 28 |
| Self initial | 39 ** | 42 ** | 30 | 31 | |
| Average | 51 ** | 38 ** | 36 * | | |
| Consensus trim 1 | 47 ** | 34 | | | |
| Egocentric trim 1 | 31 | | | | |


**Condition 2:  5 opinions (self + 4)**          N =61

|  | Egocentric trim 1 | Egocentric trim 2 | Median | Consensus-based trim 2 | Consensus-based trim 1 | Average | Self initial |
|---|---|---|---|---|---|---|---|
| Midrange | 61 ** | 57 ** | 55 ** | 57 ** | 49 ** | 58 ** | 37 |
| Self initial | 39 * | 42 ** | 35 | 34 | 33 | 31 | |
| Average | 54 ** | 49 ** | 49 ** | 51 ** | 37 | | |
| Consensus trim 1 | 48 ** | 42 ** | 47 ** | 41 ** | | | |
| Consensus trim 2 | 49 ** | 38 | 42 ** | | | | |
| Median | 38 | 35 | | | | | |
| Egocentric trim 2 | 32 | | | | | | |

Table 5 (continued)

*Which Rule Best Explains the Influence of Advice?  Pairwise Comparisons (Sign Tests) of rules (entries show the*

*number of times the column rule outperforms the row rule; * 5% ;  ** 1%)*

**Condition 3:  9 opinions (self + 8)**          N =54

|  | Egocentric trim 2 | Egocentric trim 1 | Self initial | Median | Consensus-based trim 2 | Consensus-based trim 1 | Average |
|---|---|---|---|---|---|---|---|
| Midrange | 53 ** | 51 ** | 39 ** | 48 ** | 48 ** | 46 ** | 51 ** |
| Average | 48 ** | 50 ** | 30 | 44 ** | 38 ** | 33 | |
| Consensus trim 1 | 46 ** | 45 ** | 29 | 41 ** | 33 | | |
| Consensus trim 2 | 47 ** | 48 ** | 30 | 39 ** | | | |
| Median | 40 ** | 37 ** | 28 | | | | |
| Self initial | 30 | 29 | | | | | |
| Egocentric trim 1 | 43 ** | | | | | | |

Table 6

*Regressions Predicting Final Estimates from Initial Estimates and Advice*

| Participants' knowledge | Regression Coefficients | | | $R^2$ | Utilization Coefficients | | |
|---|---|---|---|---|---|---|---|
| | Self initial | Near advice | Far advice | | Self initial | Near advice | Far advice |
| High (n=38) | 0.57 | 0.35 | 0.10 | 0.97 | 0.0177 | 0.0116 | 0.0069 |
| Low (n=37) | 0.39 | 0.38 | 0.23 | 0.96 | 0.0128 | 0.0079 | 0.0161 |
| Overall (n=75) | 0.49 | 0.37 | 0.16 | 0.97 | 0.0153 | 0.0098 | 0.0115 |

Table 7

*Weight of Own Opinion as a Function of Participant's Knowledge*

Participant's Knowledge

|  | High (n=38) | Low (n=37) | Overall (n=75) |
|---|---|---|---|
| mean | 0.83 | 0.60 | 0.71 |
| sd | 0.34 | 0.52 | 0.45 |

Table 8

*Weight of Own Opinion as a Function of Advice Condition*

*Advice condition: Location of near and far advice relative to the truth*

|  | Both away from truth | Both toward truth | Near toward truth (far away) | Far toward truth (near away) |
|---|---|---|---|---|
| mean | 0.63 | 0.54 | 1.01 | 0.67 |
| sd | 0.30 | 0.30 | 0.47 | 0.55 |