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Testing the scenario hypothesis: An experimental comparison of scenarios and forecasts for decision support in a complex decision environment

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A R T I C L E I N F O

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A B S T R A C T

Decision support tools are known to influence and facilitate decisionmaking through the thoughtful construction of the decision environment. However, little research has empirically evaluated the effects of using scenarios and forecasts. In this research, we asked participants to recommend a fisheries management strategy that achieved multiple objectives in the face of significant uncertainty. A decision support tool with one of two conditions—Scenario or Forecast—encouraged participants to explore a large set of diversified decision options. We found that participants in the two conditions explored the options similarly, but chose differently. Participants in the Scenario Condition chose the strategies that performed well over the full range of uncertainties (robust strategies) significantly more frequently than did those in the Forecast Condition. This difference seems largely to be because participants in the Scenario Condition paid increased attention to worst-case futures. The results offer lessons for designing decision support tools.

1. Introduction

Which is better for decision support: scenarios or probabilistic forecasts? Those designing decision support systems for complex decision problems often face this question when considering how best to characterize uncertainty for their users. Some commentators stress the importance of probabilistic forecasts, arguing that decisionmakers ultimately need this information to choose wisely among options.[1] In this view, scenarios are merely an intermediate stage in a hierarchy of increasingly more comprehensive uncertainty characterizations that culminate in probabilistic forecasts. Others argue that scenarios (defined in more detail below) represent a fundamentally different approach to uncertainty characterization. In this view, scenarios help decisionmakers expand their understanding of the challenges they face. As claimed by a pioneer of the method, “scenarios can change decision makers' assumptions about how the world works, compelling them to reorganize their mental models of reality (Wack, 1985a,b)”. This paper reports on a laboratory experiment that examines the influence of using scenarios versus forecasts as part of decision support tools in complex decision environments.

The selection among scenarios or forecasts represents an example of choice architecture. As is well known, the design of decision support tools can influence and facilitate decisionmaking through the thoughtful construction of the decision environment (see, e.g., Johnson et al., 2012). The way information is presented can affect, for instance, how intuitively or systematically users process information (Kahneman, 2011), what they regard as default options, their focus on worst cases, and their willingness to

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[1] See, for instance, the long-standing debate in the climate change assessment literature on the merits of placing probabilistic forecasts on scenarios (Parson et al., 2007). One school argues that decisionmakers require information on the relative likelihood of scenarios to make decisions and, as the best source of such probabilistic forecasts, experts have a responsibility to provide them (Schneider, 2001; Morgan and Keith, 2008). Others oppose placing probabilities on scenarios, arguing that such information would undercut the scenarios' cognitive and organizational benefits (Grubler and Nakicenovic, 2001; Dessai and Hulme, 2004).

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invest in protective measures (Kunreuther et al., 2014). However, studies that experimentally contrast the effects of using scenarios and forecasts in decision support tools are rare, because the literature on scenarios and forecasts emphasizes differences between the two approaches that are difficult to capture in an experimental setting.

To understand these differences, it is useful to consider the broad set of elements that are often key to an effective decision process.[2] These elements can be usefully grouped into a set of *choice* tasks that includes selecting the best decision among a menu of available options, given estimates of their consequences, and a set of *decision structuring* tasks that includes defining the problem in a way that opens it up to thoughtful consideration, defining the objectives to be achieved, and assembling a menu of options that might achieve those objectives. Note that the literature uses the term *decision structuring* in two ways: (1) as an equivalent to the term choice architecture, meaning choices made by decision analysts in how to present information to decisionmakers (e.g., von Winterfeldt, 1980); and (2) as choices by the decisionmakers themselves in what factors to highlight and which to ignore (e.g., Parker and Fischhoff, 2005; Del Missier et al., 2014). This study uses the latter meaning of the term and notes that experimental environments that present users with both decision structuring and choice tasks may highlight more differences between forecasts and scenarios than would experiments that present choice tasks alone.

The literature makes clear that probabilistic forecasts provide a powerful foundation for choosing among alternative decision options under conditions of uncertainty. Such forecasts use a single joint probability distribution to represent the likelihood of alternative future states of the world. When uncertainties are well-characterized, probabilistic forecasts provide both a concise summary of what is known and the normatively correct basis for choice among options (Morgan and Henrion, 1990). But the literature also makes clear that in at least some contexts probabilistic forecasts can prove less effective in helping decisionmakers structure the decision situations they face. For example, some people misinterpret very small probabilities, either overestimating the risks they imply or sometimes ignoring them entirely (Camerer and Kunreuther, 1989; Kahneman and Tversky, 1979). More broadly, a narrow framing of complex decisions can cause problems for individuals and in groups when the uncertainty and other features are not well structured (Tversky and Kahneman, 1981; Russo and Schoemaker, 1989; Gigone and Hastie, 1993; Levin et al., 1998). Using a single joint probability distribution may lead decisionmakers to believe they understand risks better than they do. It may also heighten disagreement among parties to a decision with differing policy preferences who may very well understand that the recommendations from the analysis will be driven by the choice of probability distribution.

The scenarios literature is more sprawling and less structured than the literature on forecasts (EEA, 2009; Wright et al., 2013a, b), but it tends to focus on benefits related to helping decisionmakers structure the decisions they face. One popular definition characterizes scenarios as descriptions of plausible future conditions presented as plausible and worthy of consideration to users faced with a challenge of decisionmaking under uncertainty (Parson et al., 2007). Such scenarios may offer strengths, including simplicity, concreteness, and an ability to foster consensus among people with differing worldviews and policy preferences. Complex and contentious policy issues can generate significant cognitive load, particularly under conditions of deep uncertainty, defined here as the condition in which decisionmakers do not know, or do not agree upon, the predictive models that relate action to consequences and the probability distributions on key parameters of those models (Lempert et al., 2003). Under such conditions, the psychological and social costs of considering futures with implications seemingly inconsistent with ones' policy preferences and values can complicate an appropriate framing (Kahan and Braman, 2006; Jones et al., 2014). Scenarios may help counteract such pressures by presenting alternative futures as possibilities rather than firm predictions, thus making them psychologically less threatening to those holding different worldviews and making it easier for decisionmakers to consider a wider range of potentially inconvenient or contentious futures, as well as new decision options that might effectively address them (Schoemaker, 1993). In particular, scenarios may help decisionmakers identify robust options that perform well compared to the alternative over a wide range of futures (van der Heijden, 1996). Relatedly, scenarios may naturally draw greater attention to small-probability, high-consequence outcomes, which are often under-attended to by decisionmakers (Slovic et al., 1977; Kunreuther, 1978). However, the concreteness of scenarios may also mislead decisionmakers into believing that low-probability futures are more likely than there is any good reason to believe that they actually are (Morgan and Keith, 2008). In addition, scenarios may prove insufficient for effective choice, in that decisionmakers may ultimately require information about the probabilities of alternative futures to choose among alternative decision options.

Overall, the literature includes claims that scenarios, in contrast to forecasts, can describe uncertainty about the future in a way that decisionmakers find easy to understand, can reduce overconfidence, and encourage individuals and groups to reflect on a broader range of futures and decision options than they might otherwise consider (Wack, 1985a,b; van der Heijden, 1996; Bishop et al., 2007; Wright et al., 2013a,b).

Based on such observations from the literature, and our own experience using decision support tools to help policymakers make decisions, we offer what we call the scenario hypothesis:

> *Decision support processes that employ scenarios, as opposed to probabilistic forecasts, to characterize deep uncertainty will help decisionmakers consider a wider range of futures and attributes, and this broader vantage will encourage the choice of more robust options that perform reasonably well in a wide range of futures.*

To test this scenario hypothesis, we conducted a laboratory experiment that tasked participants with both structuring the decision they faced and then choosing among the resulting options. To do so, we created an experimental setting that encouraged participants to explore a large set of diversified decision options and gave them considerable freedom in what decision options to consider and in how they structured the comparisons among them. The decision context is purposely complex; the intent is to simulate the high cognitive load people often face in the real world. We chose this configuration because while much of the experimental judgment and decision making (JDM) literature relevant to uncertainty characterization is attentive to context, it often focuses on choices among a small menu of fixed decision options. However, many real-world decision challenges involve a larger, more fluid set of options, such that a critical decision task is ascertaining the appropriate set

[2] Different views exist on how to characterize these elements (e.g., Parker and Fischhoff, 2005; Yates and Tschirhart, 2006). A useful taxonomy, and one motiving the current research, comes from the National Research Council (2009) and includes defining the problem, having clear objectives, having alternatives linked to those objectives, assessing consequences, and confronting tradeoffs.

to consider and how they ought to be compared.[3]

In our experiment, participants were given a web-based interactive decision support tool and asked to recommend a management strategy for a fishery that balances economic and environmental objectives under conditions of uncertainty. The decision support tool allowed participants to construct alternative management strategies one at a time using a set of radio buttons to specify various components of the strategies. Participants could then run a simulation model that displays a resulting time series for fishery profits and fish population sizes (the economic and environmental objectives, respectively) resulting from the management strategy and save and compare selected strategies in a multi-attribute comparison table. The instructions highlighted uncertainty and potential diverging interests among people concerned with economic and environmental objectives. Participants were asked to recommend the “best” strategy for their community but were given no guidance on appropriate levels of economic and environmental performance. As part of their decision structuring challenge, participants could only discover what levels were achievable by experimenting with various strategies.

The decision tool presented uncertainty on the performance of management strategies using either Forecasts or Scenarios, manipulated experimentally. The former displayed probabilistic forecasts based on what were described as experts' best estimates. The latter displayed three individual scenarios, described as representing a range of views within the community. We found that participants in both conditions made reasonable choices, examining and choosing strategies that performed generally well over most futures for both the economic and environmental objectives. Furthermore, participants in the two conditions explored the space of options similarly, but in the end, participants chose differently. Consistent with the scenario hypothesis, we found that participants in the Scenario Condition chose the strategies that performed well over the full range of uncertainties (what we call, robust strategies) significantly more frequently than did those in the Forecast Condition. This difference seems largely to be because participants in the Scenario Condition paid increased attention to worst case futures.

The next section describes the experiment in more detail. The third section describes our results. The final section describes implications for using scenarios and forecasts in decision support, what we have learned about the underlying psychological mechanisms at play, and next steps for future research.

2. Study design

In designing an experiment to test the scenario hypothesis, we faced two important challenges. We needed to present participants with a non-trivial decision-structuring task and also provide them with Forecast and Scenario Conditions that presented similar information about the decision challenge, albeit in different ways.

We addressed these challenges by posing a fishery management problem with four important characteristics:

1. Multiple objectives, including both good profits for the fishing industry and preserving a sufficient fish population;
2. Significant uncertainty about the outcomes of any given management strategy, including “worst case” futures in which most strategies cause the fishery to collapse;
3. A large and complicated set of potential decision options (i.e., management strategies) that required a significant amount of effort to explore;
4. Only a small fraction of the available strategies (about 25 percent) that perform well for both objectives over many futures (but not the worst cases) and an even smaller number of strategies (5 percent) that perform well across the entire range of uncertainty (that is, were robust across diverse futures, including the worst cases).

The decision challenge was communicated to participants through both instructions and in the design of the decision support tool. In particular, the decision support tool offered participants 79 alternative management strategies, which they could choose among by clicking on a series of radio buttons on the display. As described in more detail below, the radio buttons allowed participants to choose a regulatory instrument; a level for that instrument; whether they wanted a static or adaptive management strategy; and, if the latter, how the strategy would monitor trends and how it would adapt to those observations. This large and complicated set of decision options aimed to create a non-trivial decision-structuring challenge.

Once participants had specified a strategy, they could click on a button that would run a simulation model and have the decision support tool display the resulting time series for fishery profits and fish population sizes. The Forecast Condition would display these time series as a mean value, a probable range (one standard deviation), and, if requested by the participant, an extreme range (5th to 95th percentiles). The Scenario Condition would show the resulting time series for each of three carefully selected scenarios, with no information provided about their likelihood. To ensure that participants in both conditions had access to similar information, we designed the model, chose the probability distribution, and selected the scenarios so that the strategies that lay on or close to the Pareto frontier between the economic and environmental objectives in each of the scenarios were similar to the strategies that lay on or close to the Pareto frontiers at various percentile levels when using the probabilistic forecasts. More details on scenario selection is presented in Section 2.1.

The remainder of this section describes the decision tool interface seen by users, the information in that tool, the experimental procedure, and the specific hypotheses we tested.

2.1. Information in the decision support tool

The decision support tool simulates the 79 alternative management strategies, summarized in Table 1. Each strategy consists of one of four alternative regulatory instruments: open access, catch limits, fleet size, and individual quota. For all but open access (the default), each regulatory instrument has a low or high alternative level (for instance, a catch limit of 20,000 versus 40,000 fish) and can be implemented with or without a monitoring option. If implementing with monitoring, strategies differed by the frequency of monitoring the fish population, the observed fish population level that would trigger a regulatory response, and how sharply the allowable catch/fleet/quota would be reduced if the population trigger level were observed.

To relate the management strategies to population and economic outcomes, we used a modified version of the Fournier and

[3] For instance, the U.S. Bureau of Reclamation's Colorado Basin Study (Groves et al., 2013), conducted with decision support tools whose design helped inspire this research, involved participants with diverse interests; those interests were reflected by 26 competing objectives, considering an evolving set of hundreds of alternative policy options and four fundamentally different ways to view future climate change that resulted in roughly a thousand different projections of future hydrologic conditions.

Table 1
Components of alternative management strategies.

Regulation		Adaptive options		
Instrument	Level	Monitoring frequency	Population trigger	Adaptive response
1. Open access	n/a	n/a	n/a	n/a
2. Catch Limit 3. Fleet size 4. Individual quota	1. Low 2. High	1. No monitoring	n/a	n/a
		2. 1 year 3. 5 years 4. 10 years	1. Low 2. High	1. Low 2. High

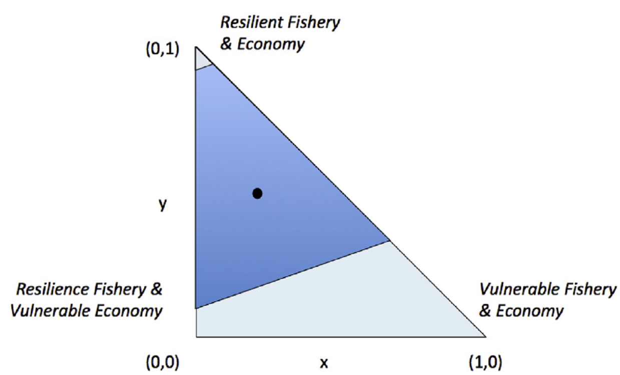


Fig. 1. Range of futures considered in the experiment.

Archibald (1982) model to simulate the population dynamics and a simple model of fishery economics. [4] The model has three uncertain parameters affecting the fish population (fish mortality rate, egg survival rate, and a mortality rate from fishing beyond which the population cannot survive) and two uncertain parameters affecting the economics of the fishery (efficiency of the fishers and the price of fish). We built the simulation model in Analytica.[5]

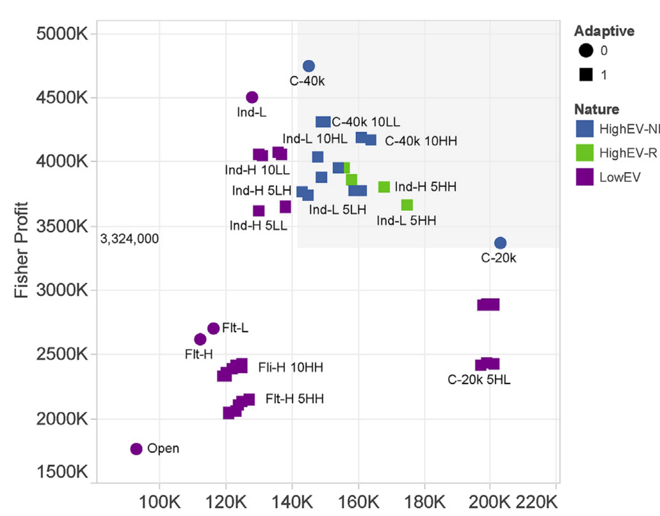
To help craft Scenario and Forecast Conditions with similar information content, both were developed by varying the uncertain model parameters linearly over a triangular uncertainty space,[6] as shown in Fig. 1.

To create the Scenario Condition, we situated one scenario at each vertex of the triangle. We called these scenarios: (1) *Resilient Fishery and Economy*, (2) *Resilient Fishery and Vulnerable Economy*, and (3) *Vulnerable Fishery and Economy*. In the first scenario, the parameters affecting the fish population and fishery profits were both at the favorable end of their range. In the second, the parameters affecting the fish population were at the favorable end and those affecting the fishery profit were at the unfavorable end of their range. In the third, both the population and profit parameters were at the unfavorable ends. This third vertex represents the worst case for the fishery. In the Scenario Condition, the decision support tool would show the resulting time series for three sets of model runs, corresponding to the three vertices of the triangle.

To create the Forecast Condition, we laid an exponential probability distribution over the region in Fig. 1. The distribution was chosen such that most of its weight lay near the *Resilient Fishery and Economy* (0,1) vertex. Only 5 percent of the weight lay near the *Vulnerable Fishery and Economy* (1,0) vertex. As shown in the figure, the centroid of the distribution lies at the point (x,y) = (0.34, 0.53) (the black dot); the one standard deviation range covers the upper two thirds of the region (dark blue region), and the 5%–95% range (light blue) covers the entire triangular region. In the Forecast Condition, the decision support tool would display the mean and selected percentile ranges for the time series as calculated by averaging model runs weighted with this exponential distribution.

Appendix A provides more details on the simulation model, the parameters that described the strategies, the parameter values that describe the uncertainties, how they vary across the region, the exponential probability distribution, and how we run the model to provide results in the decision tool.

Fig. 2 shows the expected profit and expected population, each over a 30-year time period, for the alternative strategies as calculated by the simulation model and using the exponential probability distribution. Strategies are labeled using a code that follows the layout of Table 1. For instance, C-40k is a static strategy using a Catch Limit regulatory instrument with a high level of allowed catch. Ind-L 5HH is an adaptive strategy using an Individual Quota regulatory instrument with a low-level, five-year monitoring frequency, a high population trigger, and high level of response if the triggering level is observed. Note that most Catch Limit strategies



Note: Colors show strategy category (HighEV-R, HighEV-NR, LowEV), shape indicates adaptive or static, and shaded region shows HighEV strategies.

Fig. 2. Expected profit and expected population of the 79 strategies. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

[4] The Fournier and Archibald (1982) population dynamics model tracks catch, recruitment, natural mortality, and fish population over time, given a catch limit specified by the participants. The model was augmented to include an uncertain threshold, related to fishing mortality for spawning females, below which juvenile recruitment will drop rapidly, leading to an overall population crash. This model is detailed enough to provide realistic results and lead to non-linear divergent outcomes in different scenario conditions, while retaining an inherent simplicity to facilitate the experiment.

[5] http://www.lumina.com/products/analytica-editions/.

[6] Each point in the triangular region is a five-dimensional vector of uncertain parameter values, expressible as a linear combination of the vectors at each of the vertices.

lie along the Pareto frontier showing the strategies with the best combinations of expected profit and population outcomes. Two static strategies, C-40k and C-20k, yield the highest expected profit and population, respectively.

Fig. 2 suggests how the strategies divide into three categories consistent with the desired attributes of the decision challenge listed at the start of this section. We call these categories: robust high expected value (HighEV-R), non-robust high expected value (HighEV-NR), and low expected value (LowEV). We define High EV strategies as those that lie close to the Pareto frontier for expected profit and expected population. In particular, we define such strategies as those within 70 percent of the highest possible expected profit and population, respectively.[7] As shown in the upper right hand corner of Fig. 2, this definition yields eighteen High EV strategies (about 25 percent of the total of 79). Among these eighteen are four (5 percent) HighEV-R strategies, which have non-zero fish population across the entire region shown in Fig. 1, including the lower right-hand vertex representing the worst-case future. However, the expected value performance of the HighEV-R strategies lies slightly interior to the Pareto frontier. Thus, these strategies represent robust strategies in the sense of trading some optimal performance for less sensitivity to broken assumptions (Lempert and Collins, 2007). For the other fourteen HighEV-NR strategies, the fish population falls to zero in this worst-case future. We categorize the remaining 61 strategies as LowEV.

As shown in Fig. 2, two of the HighEV-NR strategies are static (i.e., those without monitoring) and sixteen are adaptive (i.e., those that include monitoring). All four HighEV-R strategies are adaptive.

The experiment was designed so that the three scenarios from the Scenario Condition—the *Resilient Fishery & Economy*, the *Resilient Fishery & Vulnerable Economy*, and the *Vulnerable Fishery & Economy*—correspond to the 67th, 33rd, and 5th percentile futures from the Forecast Condition, as can be seen earlier from Fig. 1. Thus, the strategies along and close to the Pareto frontiers are similar in each of these pairs of scenarios/forecasts. The Scenario Condition has no analogue to the Forecast Condition's expected future (Fig. 2), but the ordering of strategies along the Pareto frontiers in the 67th and 33rd percentiles, and their related scenarios, is mostly similar to that in the expected future. In contrast, for the 5th percentile and its related scenario, the Pareto frontier consists only of the HighEV-R strategies, which are the only ones that do not drive the fish population to zero. This similarity of strategies that lies near the Pareto frontiers in the corresponding scenarios and Forecast Condition percentiles indicates that the two conditions provide similar information.

Appendix B provides more detail on the information presented in the two conditions.

2.2. Decision tool as seen by participants

The instructions provided to participants asked them to imagine they lived in a coastal community with a fishery that is important both economically and environmentally. Participants were tasked to use the decision support tool to recommend a fishery management strategy for their community. The instructions emphasized that overfishing represented one of the most important threats to fisheries and that, thus, they needed to choose a strategy that balances both economic and environmental objectives. The instructions noted that while these objectives often conflict, the existence of profitable and sustainable fisheries suggests that an appropriate balance can be achieved.

Uncertainty, however, complicates the participants' ability to find a strategy with an appropriate balance between the two objectives. The instructions explicitly mentioned the uncertain factors affecting the fishery and informed participants that these uncertainties would affect the fishery profit and fish population resulting from any fishery management strategy.

Fig. 3 shows the computer decision support tool provided to participants to help them recommend an appropriate fishery management strategy, including the controls and sample displays seen by participants in the Scenario (upper panel) and Forecast (lower panel) Conditions. It allowed users to select strategies for consideration one, run those strategies in the simulation model, view the resulting time series for fish population and fishery profit, and decide whether to save the results in a summary table.

The radio buttons at the lower left allow users to specify one of the strategies shown in Table 1. Note that choosing one of the 7 static strategies involves clicking on a single radio button. Choosing one of the 72 adaptive strategies was more complicated. Doing so involves clicking on five radio buttons: one specifying the regulatory instrument and its level, one asking for monitoring, and one each for the monitoring frequency, the population trigger level, and the aggressiveness of the adaptive response. Once participants choose a strategy, they can press the RUN button, which causes the resulting population and profit time series to appear in the displays, unfolding from left to right. The RESET button clears the display. The purple CHOOSE button in the upper right allows users to report their chosen strategy.

To facilitate comparison among the strategies, the SAVE button stores the final fish population and 30-year cumulative profit in the summary table at the top of the screen. Buttons to right of the table allow users to delete an entry, make notes, and display it again. Vertical slider bars to the right of each time series display allow users to select thresholds that determine the green, yellow, and red coloring of the entries in the table. This summary table was designed to help participants structure a choice set. For instance, through repeated exploration, a participant in the Forecast Condition might populate her table with strategies that lie near the expected Pareto frontier in Fig. 1 and then use this table to choose among them.

The intent was to create a non-trivial but feasible decision-structuring task. Since there were more strategies than most people would have patience to run or that could be consciously considered at once, participants had to choose which strategies to run, which to save, and how to color-code the table to highlight the profit and population tradeoffs among those strategies. The tool, and the supplementary information and instructions, were iteratively developed and refined based on pilot-tests with non-technical members of the general public.

The Scenario and Forecast Conditions emphasized some of the differences between scenarios and probabilistic forecasts. In the Scenario Condition, participants were told that people disagree on the how likely each of the uncertain factors might be. Fishery experts thus worked with the community to develop three scenarios that represent the range of views within the community, as displayed in the decision tool. In the Forecast Condition, participants were told that people disagree on the value of the uncertain factors. Fishery experts were thus asked to estimate the likelihood of various values in making their predictions. The decision support tool included the estimate the experts believe is most likely, as well as a range around the most likely estimate that accounts for uncertainty in all these uncertain factors.

Participants in the two conditions also saw slightly different displays. In the Scenario Condition, the time series displays for

[7] With this definition, the expected profit of any HighEV strategy is at least as large as the lowest expected profit strategy on the Pareto frontier (C-20k), and the expected population of any HighEV strategy is at least as large as the lowest expected population on the frontier (C-40k).

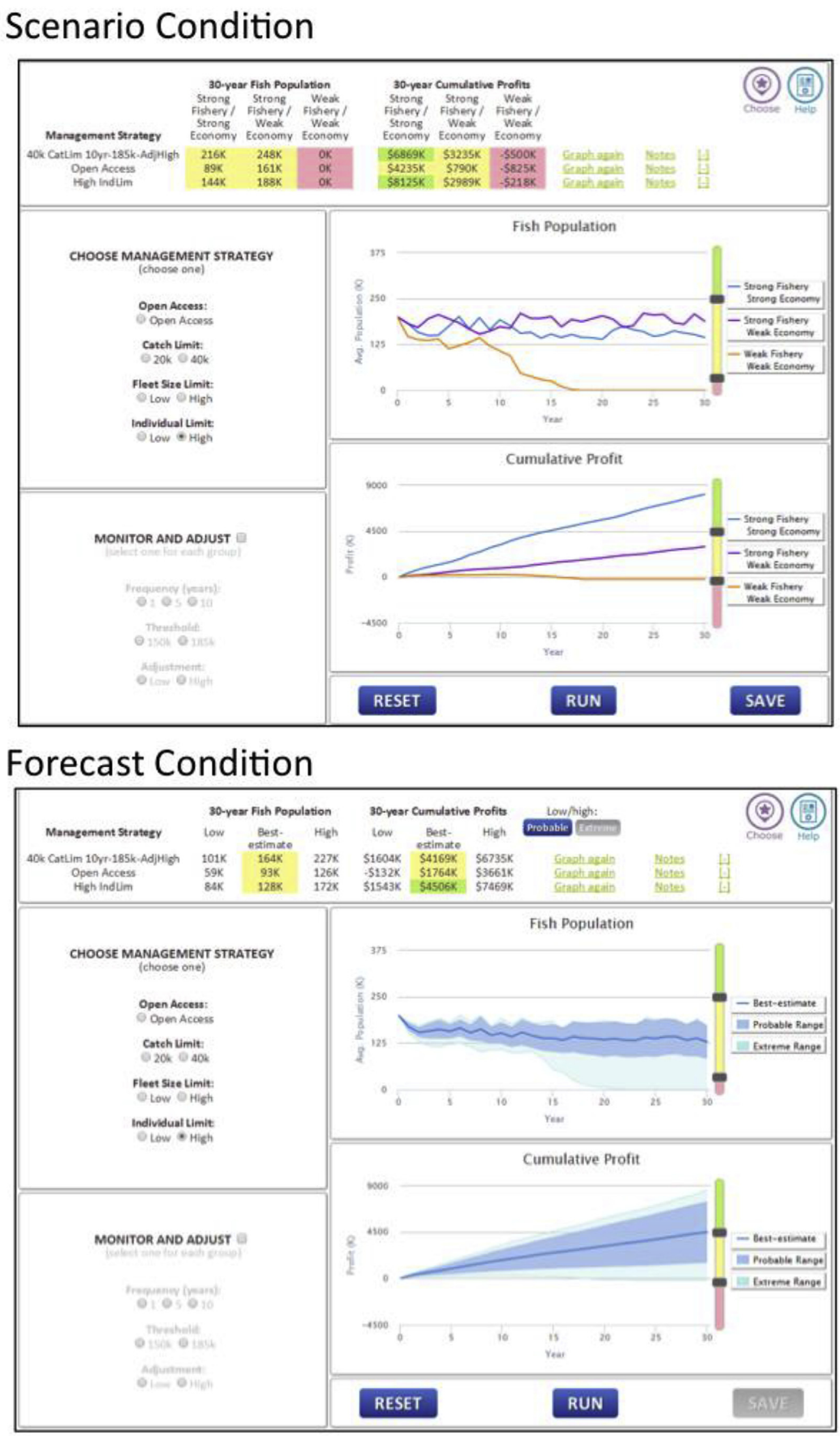


Fig. 3. Screenshots of the decision tool in the scenario and forecast conditions.

population and profit had separate lines for each of the three scenarios. The scenario condition summary table (top of the screen) also had columns for each of these scenarios. In the Forecast Condition, the time series displays showed the mean and high and low values for the "probable" range (one standard deviation) for population and profit. Participants could choose to also view the high and low values for what was called the "extreme" range (5 percent–95 percent). The forecast condition summary table had columns for the mean and for the high and low values for either the probable or extreme range as chosen by the user.

2.3. Experimental procedure

The laboratory experiment used a 2 (Decisionmaker: Individual or Dyad) by 2 (Presentation Mode: Scenario or Forecast) between-subjects design.

Sample: The study was run in the behavior labs at two Northeastern universities; in total, 471 participants completed the web-based study. Four participants were dropped because of a mechanical failure that prevented the experimenter from saving the data. The data presented in this paper are from the remaining 467 participants.

Participants either completed the study as an individual or as a dyad that had to reach a consensus decision. In the individual conditions, participants were told to provide advice to a community board that valued both fishing profit and fish population. In the dyad conditions, one participant was told to represent the economic interests of the fishers, while the other one was told to represent the interests of the environmentalists. We considered dyads to explore the differential effects of scenarios and forecasts on individual and group choices. Participants represented both roles reasonably well, according to the self and partner evaluation in the post-study survey. As shown in Table 2, participants were distributed roughly equally among the four conditions.

Procedure: Participants used a laboratory computer to complete the study. The computers were placed in separate stations surrounded by cardboard to provide privacy. Participants/dyads were approximately six feet apart. Dyad discussions were audio-recorded with the consent of the participants. Each participant in the dyad conditions completed the post-experiment questionnaires on their individual computer, but used a third computer when going through the training session, using the decision tool to run simulations or make final decisions.

Prior to using the interactive tool, participants were provided with a step-by-step interactive tutorial, which walked them through the various components of the tool, including viewing the extreme ranges. Participants had unlimited access to the decision tool and could simulate and compare as many strategies as they wished before reporting on their final decision. They were told that if they did not choose a strategy, because, for instance, of an impasse in the dyad conditions, "open access" would be their default choice. However, all participants were able to make or reach a final decision.

After making the final choice, participants were directed to fill a post-experiment questionnaire that included questions about their experience with the decision tool, self-reports on their individual and (in the dyad) group decision process, their attitudes on environmental and free-market issues, and demographics. Appendix C describes the survey and lists the questionnaire.

The entire study took 40–60 min to finish for most participants. Participants were paid a nominal fee ($10 or $15, depending on in which of two laboratories they participated).

Table 2
Number of decision makers in each of the four conditions.

	Individual	Dyad	Total
Forecast	88	73 (146 participants)	161
Scenario	87	73 (146 participants)	160
Total	175	146 (292 participants)	321 (467 Participants)

2.4. Hypotheses

We decomposed the scenario hypothesis into four specific behavioral hypotheses that we used this experiment and its decision tool to test.

Participants were asked to advise a community that values both fishery profits and fish population. The HighEV strategies generally dominate the others for both these measures. We thus predict:

H1. Participants will tend to choose one of the 18 HighEV strategies.

The Forecast Condition presents probabilistic information, while the Scenario Condition does not (Schoemaker, 1993). This should make it easier for those in the Forecast Condition to identify HighEV strategies. We thus predict:

H2. Participants in the Forecast Condition are more likely to choose one of the 18 HighEV strategies than those in the Scenario Condition.

Scenarios, more so than forecasts, incline users to consider a wider range of futures (Schoemaker, 1993; Kuhn and Sniezek, 1996). This broader perspective should facilitate choosing strategies that are robust across multiple futures. We thus predict:

H3. Participants in the Scenario Condition are more likely to choose one of the four HighEV-R strategies than those in the Forecast Condition.

Scenarios also aim to encourage people with competing interests and differing worldviews to agree on a set of futures to consider without necessarily agreeing on their relative likelihood. Participants in the dyads were each asked to represent the economic interest of the fisheries or the environmental interest of the fish population. The experiment forced tradeoffs between these two objectives. In the dyad, this could potentially create conflict between the individuals asked to advocate for the differing objectives. In the presence of such conflict, we expect that the Scenario Condition would prove more effective in helping groups reach consensus on a strategy (Schwartz, 1996; van der Heijden, 1996). We thus predict:

H4. The difference in HighEV-R strategy selection between the Scenario and Forecast Condition is larger for dyads than it is for individuals. That is, there will be a statistical interaction between participant type and presentation mode.

3. Results

As shown in Table 3, participants from two laboratories differed significantly on several characteristics, including gender, education, and attitudes toward the environment and free markets. We included these as control variables in our analysis of final strategy selection, although none of them were significant predictors in those analyses.

Table 4 presents decision effort and final choice, broken out by Laboratory. As with demographics, the two subsamples differed significantly in several measures of decision effort, including time on task, number of notes, and use of the notes function. They did

Table 3
Participant demographics, by laboratory.

		Lab 1 (294 participants)	Lab 2 (173 participants)	Statistics	p-value
Subjects	Gender (Male)	43%	30%	$X^2(1) = 7.10$	<0.01
	Education (BA)	31%	15%	$X^2 (4) = 24.4$	<0.01
	Education (MA or above)	18%	13%		
	Age (18–27)	86%	86%	$X^2 (5) = 10.1$	0.07
	Mean NEP	54 out of 75	52 out of 75	$t(329) = 2.78$	<0.01
	Free-market	13.1 out of 30	13.7 out of 30	$t(349) = 1.68$	0.1

Table 4
Decision effort and final choices, by laboratory.

		Lab 1	Lab 2	Statistics	p-value
Decision Effort	Decision Time	12 min	9 min	$t(433) = 6.45$	<0.01
	Total Runs	20	15	$t(456) = 5.68$	<0.01
	Unique Runs	15	10	$t(463) = 6.56$	<0.01
	Left Notes	20%	5%	$X^2 (1) = 18.8$	<0.01
	Sliders	66%	59%	$X^2 (1) = 2.24$	0.13
	Extreme Range	15%	15%	$X^2 (1) = 0$	1

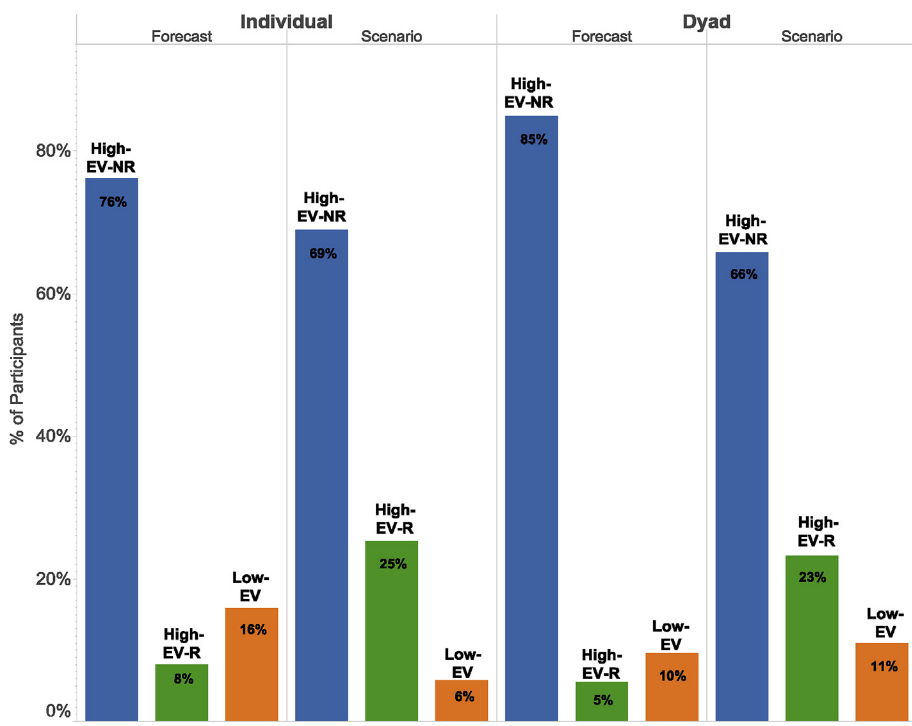


Fig. 4. Participants choice of strategies.

not differ in use of the sliders or examination of the extreme range (the latter only for the Forecast Condition). That said, there were no significant differences between the two subsamples in final choices. None of the lab or participant characteristics was a significant predictor of the final choice. Hence, all further analyses collapse across the two subsamples.

3.1. Analysis of final choices by experimental condition

Fig. 4 shows the distribution of participants' final choices, broken down by individual versus dyad and Forecast versus Scenario Conditions. Consistent with H1, 90 percent of the participants chose one of the 18 HighEV strategies. A $\chi 2$ test of the proportion choosing HighEV versus a proportion of 50 percent was significant ($df = 1$, $\chi 2(1) = 291.6$, $p < 0.001$) for the full sample, as well as within the Forecast condition ($\chi 2\ (1) = 135.4$, $p < 0.001$) and within the Scenario condition ($\chi 2\ (1) = 156.6$, $p < 0.001$).

Contrary to H2, participants in the Scenario Condition chose HighEV strategies at least as frequently as those in the Forecast Condition. To test this, we conducted a logistic regression, regressing an indicator of HighEV (scored 1) versus Low EV (scored 0) onto presentation mode (scenario, scored 1, or forecast, scored 0) and decisionmaker (individual, scored 1, or dyad, scored 0), while controlling for lab space (1 or 2)[8]. The effect of presentation condition (Forecast versus Scenario) was non-significant (log odds = 0.33, SE = 0.31, ns.). Adding additional controls for demographics, environmental attitudes, and free-market attitudes had no effect on this result.

Consistent with H3, participants in the Scenario Condition chose HighEV-R strategies far more frequently than participants in the Forecast Condition. To test this, we conducted a similar regression, but with the dependent-variable indicating selection of one of the four robust strategies (HighEV-R; scored 1) versus not (HighEV-NR or LowEV; scored 0). Participants in the Scenario Condition were 19 percent more likely (marginal effect = 19 percent) to choose one of the four robust strategies than those in the Forecast Condition (log odds = 1.54, SE = 0.31; $p < 0.0001$).

Finally, to test H4, that the difference in HighEV-R strategy selection between the Scenario and Forecast Conditional is larger for dyads than for individuals, we added an interaction between presentation mode (Scenario versus Forecast) and decisionmaker (individual versus dyad) to the regression used to test H3. The interaction was non-significant (log odds = −0.28, SE = 0.62, ns.), suggesting that being in a dyad did not amplify this difference. Adding additional controls for demographics and attitudes did not change the results for H3 or H4.

3.2. Analysis of the decision process

3.2.1. Specific strategy choice

To understand how participants made their decision and how that led to their choice, it is useful to first consider the specific strategies they chose. Fig. 5 shows the individual strategies chosen in the Scenario and Forecast Conditions. Note that many strategies were never chosen and lie atop one another at the origin of the figure. Participants chose the static HighEV-NR strategies C-20K (low catch limit) and C-40K (high catch limit) roughly four times as often as the next-most chosen strategies. Participants in the Scenario Condition chose C-20K about twice as often as C-40K, and visa versa for the Forecast Condition. Three adaptive strategies were the next-most chosen strategies. Participants in the Scenario Condition preferentially choose the HighEV-R strategies Ind-L 5HH (low individual limit, monitored every 5 years, with high trigger and response) and Ind-H 10HH (high individual limit, monitored every 10 years, with high trigger and response). Participants in the Forecast Condition preferentially chose the HighEV-NR strategy C-40K10HH (high catch limit, monitored every 10 years, with high trigger and response). The choice among these three adaptive strategies largely explains the differing rates of robust strategy selection in the two conditions seen in Fig. 4.

As can be seen in Table 5, these differing choices in the Scenario and Forecast Conditions may be driven by the amount of attention paid to the extreme cases. The table shows for each of the five most-chosen strategies the profit and population in the Forecast Condition under four futures: expected, high (67th percentile), low (33rd percentile), and extreme low (5th percentile). All the five strategies are high-EV, but only two of them are also robust to the full range of futures. Note that strategy C-40Khas higher expected profit than strategy C-20K, but lower profit in the Low and Extreme Low futures. The three adaptive strategies all have lower expected profit than the static C-40K, but higher expected profit than C-20K. The reverse is true for expected population. However, the three adaptive strategies have significantly higher Low future profit and population than the two static strategies. In the Extreme Low future, the two robust strategies, Ind-L 5HH and Ind-H 10HH, have higher profit than the HighEV-NR strategy C-40K10HH or the two static strategies. Of the five most-chosen, these two strategies are the only ones that preserve the fish population in this worst case. These are also the two that are more frequently chosen in the Scenario Condition than in the Forecast Condition, as described above.

In the Scenario Condition, participants see the *Resilience Fishery & Economy* and the *Vulnerable Fishery & Economy* scenarios, which have profits and populations similar to the High and Extreme Low futures shown in Table 5. Values for the *Resilient Fishery & Vulnerable Economy* scenario are not shown in the table, but as noted in Section 2, they are similar for C-20K and more favorable for C-40Kthan the Low future values.

Recall that participants were instructed to choose a strategy that served both economic and environmental objectives. Thus, paying attention to only the expected values, participants might reasonably choose any of the strategies in Table 5, since they all lay close to the expected value Pareto frontier. But of the two static strategies, C-20K has significantly higher profit and population in the Low future than does C-40K. C-40K10HH dominates the two HighEV-R strategies in profit and dominates or is close in population in all cases other than the Extreme Low future.

In summary, the patterns of choice seen in Fig. 5 and Table 5 are consistent with two claims. First, participants are more likely to choose static than adaptive strategies, perhaps because the former are simpler to specify (one versus five radio buttons). Second, participants in the Scenario Condition are more likely to choose strategies that do better in the Extreme Low case than are participants in the Forecast Condition, perhaps because they differentially attend to this information.

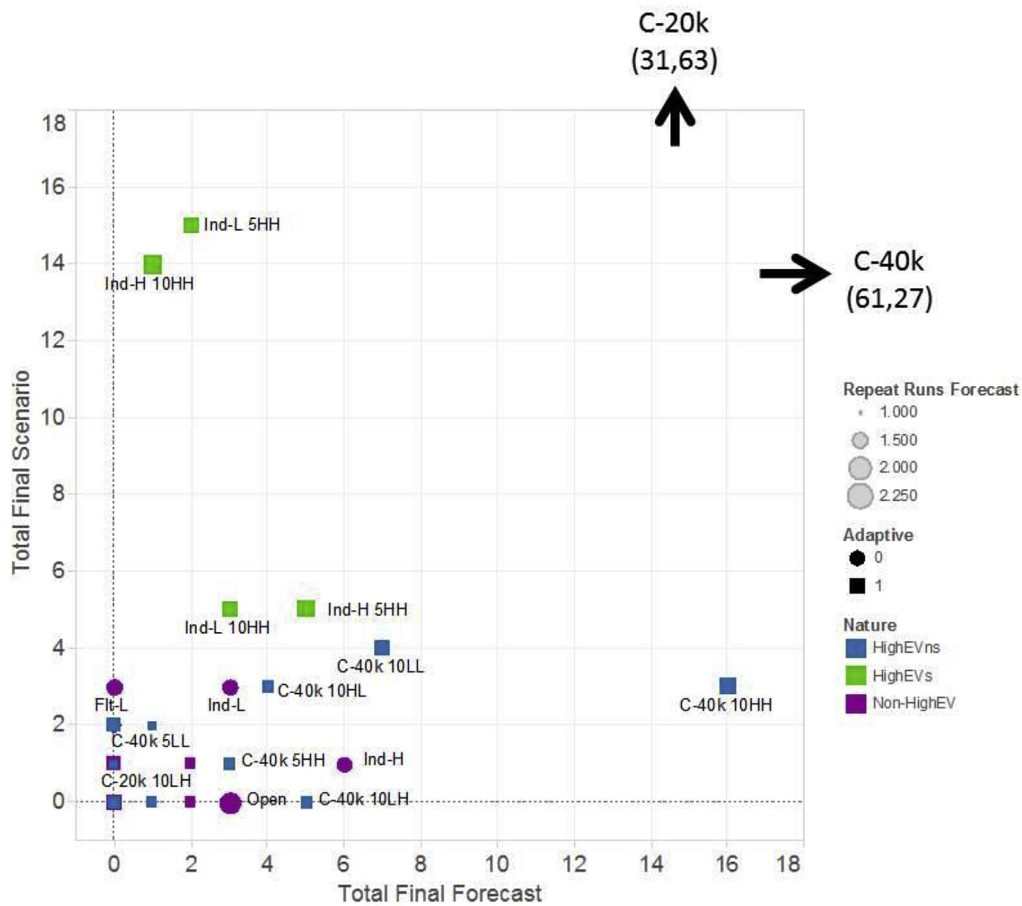
3.2.2. Strategy search

Despite their differing choices, participants in the two conditions searched the set of potential strategies in largely similar ways. We considered several measures of strategy search and focus here on the number of times participants ran the strategy and the number of repeat runs of the strategy.[9] A run of a strategy consists of defining the strategy with the radio buttons on the left panels in Fig. 3 and then clicking the “Run” button. A repeat run consists of running a strategy a second or third time. Participants can only gain information about the performance of a strategy by running it at least once. Repeat runs may represent strategies participants find particularly interesting or worth considering.

Fig. 6 shows the total number of times participants ran each of the 79 strategies, on log-linear scale, for the Forecast Condition (horizontal axis) and Scenario Condition (vertical axis). Note that participants ran the seven static strategies significantly more often than the adaptive strategies, presumably because the former were simpler to define. Participants ran the simplest strategy, Open Access, more often than any other, although they rarely chose it. In both the Forecast and Scenario Conditions, roughly a fifth of the

[8] Per a reviewer request, we also included the decision time in the regressions and found out that whether the decision time was greater than 5 min was only marginally significant in predicting whether a participant would choose a Robust strategy ($p < 0.09$). In addition, we found that all of the fastest participants who had a decision time of three minutes or less (15 participants), and 82.4% of those who had a decision time of five minutes or less (74 participants), chose a High Expected Value strategy, which is a strong indication that they were fast decision makers, rather than absent minded or confused ones. We also included the interaction term between Condition and Decision Time in the regression to predict likelihood of choosing a robust strategy, and found no significant interaction ($p = 0.98$).

[9] We also examined decision time and use of the sliders, each of which could indicate greater attention or effort. There were no significant differences across condition.



Note: Colors show strategy category (HighEV-R, HighEV-NR, LowEV), shape indicates adaptive or static, size indicates number of times strategy viewed multiple times by users.

Fig. 5. Choice of strategy in scenario and forecast conditions. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 5
Performance in forecast condition of most-chosen strategies.

	High EV, non-robust			High EV, robust	
	C-40K	C-20K	C-40K10HH	Ind-L 5HH	Ind-H 10HH
Profit					
High	\$7510 K	\$4620 K	\$6735 K	\$5938 K	\$6227 K
Expected	\$4748 K	\$3367 K	\$4169 K	\$3660 K	\$3951 K
Low	\$18 K	\$490 K	\$1604 K	\$1383 K	\$1675 K
Extreme Low	\$18 K	\$490 K	-\$429 K	\$543 K	\$754 K
Population					
High	205 K	303 K	247 K	198 K	183 K
Expected	145 K	203 K	164 K	175 K	156 K
Low	0	0	101 K	152 K	128 K
Extreme Low	0	0	0	128 K	126 K

participants never ran any adaptive strategies.[10] Among the adaptive strategies, participants generally ran the HighEV strategies

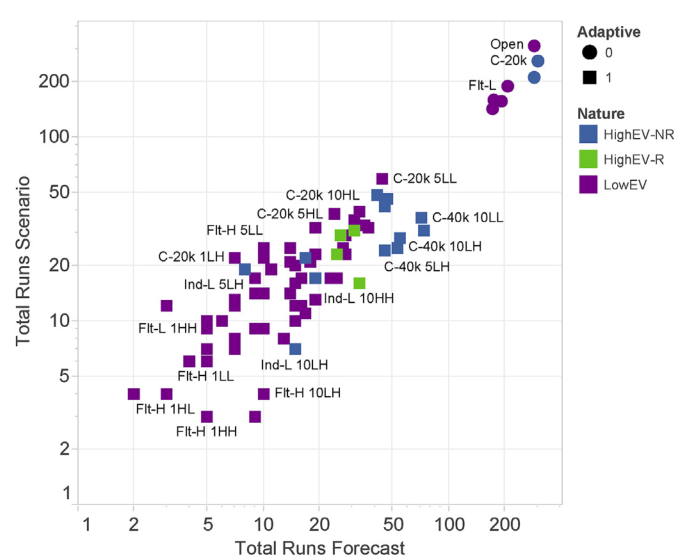


Fig. 6. Strategies simulated in scenario and forecast conditions. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

[10] To examine the behavior of those individuals who never ran an adaptive strategy, we ran additional data analyses. We found no significant difference between the two conditions on the likelihood of running adaptive strategies. Note that failing to discover an adaptive strategy does not necessarily indicate low data quality among those individuals. There are two static (non-adaptive) strategies available that have high expected value, and therefore represent reasonable choices (These strategies lie at the two extreme ends of the Pareto surface in Fig. 2.)

more often than the LowEV strategies. However, the type of strategy also seems to correlate with the number of runs. Catch Limit strategies are generally run more often than Fleet Size strategies. Most strategies cluster around the diagonal, which indicates that they were run roughly equal times in both the Scenario and Forecast Conditions. All strategies were run at least once by some participant.

The results also suggest that, with the exception of the static strategies, a higher ratio of repeat runs correlates with the more frequently chosen strategies. That is, participants tended to view multiple times the strategies they ultimately chose. Fig. 5 shows this information using the size of its markers, which show the number of repeat runs, defined as the ratio of total runs to unique runs. A value of one means that no participant who viewed a strategy ever returned to it. A higher value means participants on average viewed a strategy multiple times. Not shown in the figure is that, perhaps surprisingly, participants in the forecast condition had more repeat views of the four HighEV-R and most of the 14 HighEV-NR strategies than did participants in the scenario condition. That is, Forecast Condition participants looked at both High EV Non-robust and the robust strategies multiple times, and ultimately decided to choose the High EV Non-robust ones. In contrast, Scenario Condition participants on average chose a robust strategy with one viewing.

Finally, Table 5 suggests that C-40K10HH is a promising strategy if one excludes the extreme worst case. In the Scenario Condition, all participants saw this future. In the Forecast Condition, participants were aware they could view the extreme low future because they were required to view it in training. But during the session, Forecast Condition participants needed to opt in to see the extreme range, and only 15 percent of them did so. Those who did view the extreme range in the Forecast Condition chose robust strategies at a similar rate to participants in the Scenario Condition. Overall, participants who used the extreme ranges in the Forecast condition were 8% more likely to choose a robust strategy than those did not use the extreme ranges ($p < 0.01$). This provides additional evidence that attention to the extreme low future may explain the difference between the Forecast and Scenario Conditions.

-*The post-experiment questionnaire provides additional insight on how scenarios and forecasts affect decision structuring and choice. As described in Appendix C, participants' self-reports suggested that those in the Scenario Condition were statistically significantly more likely to visualize multiple futures rather than a single future.

4. Discussion and implications

This study tested the scenario hypothesis with an experiment that required participants to devote considerable effort to understanding a decision challenge, in particular identifying the range of futures they wished to consider, the strategies they wished to compare, and the criteria they wished to use to compare them. We hypothesized that in such a context, incorporating scenarios would incline users to consider a wider range of futures and eventually choose strategies more robust over such futures than users given probabilistic forecasts.

In both the Forecast and Scenario Conditions, participants overwhelmingly choose the High EV strategies (H1). This finding supports the validity of the experimental exercise. Despite the difficulty of the task and the complexity of the decision tool, most participants made what appear to be reasonable choices. Interestingly, and inconsistent with our expectations (H2), participants in the Scenario Condition were as likely to choose a high EV strategy as were participants in the Forecast Condition. Only participants in the latter condition were given any information about probabilities. However, the scenarios and strategies were configured such that any strategy that lay close the Pareto frontier in all three scenarios also laid close the expected Pareto frontier (see Appendix B). This configuration may explain the similar ability of participants in the two conditions to choose High EV strategies.

Consistent with H3, we found that participants in the Scenario Condition were significantly more likely than those in the Forecast Condition to choose a robust strategy, that is, one that performed well for both objectives over the entire range of futures. This is likely because the Scenario Condition included a "worst case" scenario that was difficult for participants to ignore. Participants in the Forecast Condition could access information about the performance of strategies in the wors -case, but it was harder to come by in that they needed to opt-in to view the extreme probability ranges. Only 15 percent of participants did so, although all them had been required to turn on the extreme ranges in the Instruction and Training session. High cognitive load may have discouraged Forecast Condition participants from opting in to the extreme condition display. In addition, considering extreme ranges may have also made it more difficult to find strategies that met both economic and environmental objectives. This neglect of extreme cases is consistent with previous research suggesting that people tend to ignore small probability events (Camerer and Kunreuther, 1989). Participants who turned on the extreme values were significantly more likely to choose a robust strategy than participants who never did so ($p < 0.01$). We found no evidence that this increased likelihood of choosing a robust strategy in the Scenario Condition was greater with dyads than individuals (H4).

To help understand how participants used the decision support tool, our experiment also tracked what strategies users considered and which strategies they chose. In contrast to our expectations, participants in the two conditions explored the set of strategies in similar ways. In both conditions, participants ran the simpler static strategies significantly more often than the adaptive strategies and ran the more desirable High EV adaptive strategies more often than non-High EV adaptive strategies. We had expected that Scenario Condition participants would be more successful in finding the robust strategies, because their ability to perform well in the extreme cases would be more readily apparent. But participants in both conditions considered robust strategies with equal likelihood (47 percent and 46 percent in the Forecast and Scenario Conditions, respectively), in the sense of configuring it with the radio buttons and running it through the simulation. But participants chose differently. Only 14 percent of Forecast Condition users who considered a robust strategy chose one, while half (52 percent) of Scenario Condition users did so.

The literature suggests that scenarios and forecasts may offer contrasting benefits. Scenarios may promote an increased focus on multiple, as opposed to single, futures; help make the future more concrete; and promote consensus. Probabilistic forecasts may offer an increased focus on and understanding of the likelihood of alternative futures. Our post-experiment survey aimed to evaluate how much our Scenario and Forecast Conditions prompted these benefits. Participants in the latter condition were more likely to agree with the statement "I tended to think about one vision of the futures and planned with that future in mind," suggesting that the Scenario Condition, more so than the Forecast one, encourages thinking about multiple futures. Other differences between the two conditions were not significant.

4.1. Implications for the practice and science of decision support

These results offer useful lessons for the design of decision support tools. Most basically, this experiment suggests that using scenarios, rather than forecasts, to display uncertainty can encourage users to consider a wider range of futures and to choose robust strategies. These results are consistent with claims in the literature, which up to now have not had strong experimental support. In this case at least, the scenarios appear to encourage the choice of robust strategies by focusing users' attention on extreme cases in which the robust strategies perform significantly better than the alternatives.

This research also highlights the potential inefficiency of a "full information" approach. The results on H2 and H3 suggest that although participants in the Forecast Condition had access to full information on the probability distribution, they did not benefit from it. Participants were not more efficient in identifying strategies with high expected value, as one would have expected, and they did worse in choosing robust strategies than those in the Scenario Condition. This is consistent with the satisficing and finite processing-capacity literatures (Simon, 1957; Stanovich, 2011).

Important to the findings here, and potentially relevant to decision support more generally, this experiment crafted a small set of scenarios, without reference to probabilistic information, that help users choose strategies that would also be reasonable choices had they had access to probabilistic information. This was possible because the strategies and scenarios were chosen so that some strategies lay close to the Pareto frontier in both the expected and extreme cases. Clearly, not all decision challenges will have strategies and scenarios with this characteristic. However, the literature increasingly offers quantitative "scenario discovery" decision aids that can help identify scenarios with pre-specified, decision-relevant characteristics (Bryant and Lempert, 2010, Gerst et al., 2013; Kwakkel et al., 2013; Lempert, 2013). Using such methods may help populate decision tools with scenario sets that both encourage exploration while avoiding clearly suboptimal choices.

These results also suggest the importance of including information on extreme ranges in probabilistic forecasts. Forecast Condition participants who opted to view the extreme ranges chose robust strategies at the similar rates as Scenario Condition participants.

4.2. Limitations and future directions

This study's decision support tool provided a unique platform for comparing forecast and scenario presentations in a richer decision context than has heretofore been available in an experimental setting. Because of the rich decision context used in the study, the results apply primarily to complex decision environments and may or may not extend to the simpler decision contexts common in many behavioral studies. The initial results provide useful and potentially surprising findings. But they also suggest additional questions and, in particular, how an even more deeply contextual experimental environment might provide additional insights.

First, future experiments might explore how to combine scenarios and probabilistic forecasts in decision support tools in a way that allows users to benefit from the best attributes of both. Probabilistic judgments are often contested in policy debates, in particular when it is clear that the weight assigned to extreme events can significantly influence the normative ranking of policy choices. One might imagine addressing this challenge with tools that first employ scenarios to help users craft a suitable set of decision options and only then provide probabilistic information to help users chose among the strategies (Lempert, 2013).

Second, future experiments might record and analyze significant amounts of data on the participants' process of using the tool. For instance, one might usefully examine the order in which participant considered strategies, how many strategies participants saved to the summary table, which strategies users saved, and which they subsequently deleted. One might also employ think-aloud protocols (e.g., Morgan, 2002), capturing participants' strategies in their own words, as a means of uncovering behaviorally unobservable decision considerations. Such information might provide valuable insight on how participants structured their decision and made their final choices.

Finally, this experiment offered a unique environment for comparing alternative presentations of uncertainty, but its design only scratches the surface of the rich, unstructured, deeply uncertain, and often controversial contexts that may most significantly differentiate among the potential benefits of scenarios and probabilistic forecasts. For instance, this experiment's choice set, while large, was explicitly enumerated on the tool's strategy-choice interface. This limited our ability to examine an important attribute of real-life policy challenges, namely that new solutions often emerge as a result of deliberation (Sen, 2009). Future experiments might allow participants to suggest and explore parts of the option space not initially apparent. For instance, the decision tool might hide the adaptive strategies until participants specifically ask for them. Such an approach could amplify our understanding of how different decision-support approaches can facilitate the generation of a choice set, rather than just choosing among enumerated options.

In addition, this experiment combined a large cognitive load with an opt-in for extreme cases to explore the tendency of decisionmakers to ignore low probability events. Future experiments might better represent some of the real-world pressures that may encourage decisionmakers to pay less attention to such cases. For instance, decisionmakers might perceive that hedging against extreme events would prove costly and thus seek to ignore them, in particular when the probability judgments are imprecise. Our experiment did try to mimic such pressures in the dyads by asking one participant to identify with environmentalists and the other with fisheries. The latter—presumably more concerned with the economic objective—might be more prone to ignore the worst cases than the former. However, the experiments may not have proved as contentious as they could be. Increasing group size, changing the incentive structure, and choosing participants with pre-established views might increase the potential for group conflict and, hence, provide a stronger test of whether scenarios relative to forecasts can focus attention on extreme cases and improve the performance of contentious groups. Additionally, a growing literature highlights the importance of affect in decisionmaking (e.g., Finucane et al., 2000; Slovic et al., 2005). Assessing the role of affect may help further illuminate decision processes in not only complex decision environments, but potentially contentious or affect-inducing ones.

Addressing any of these questions could provide important additional information on the implications of using forecasts and scenarios in decision support. Nonetheless, the results presented here provide a significant test of the scenario hypothesis and of a decision tool that offers a useful foundation for future work.

Appendix A. Description of the model

This appendix describes the simulation model used to generate the results in our experimental displays, the parameters used to specify the strategies, the parameter values that describe the uncertainties, how these uncertain parameters vary across the region shown in Fig. 2, the exponential probability distribution, and how the simulation was run to provide the results in the decision tool.

The simulation model, written in the Analytica modeling system, relates the ability of a fisheries management strategy to achieve objectives contingent on the values of the uncertain parameters. Fig. A1 summarizes the main components of the simulation, which uses a traditional bioeconomics model to evaluate the dynamics of a single species fishery with homogeneous fishing fleets. The simulation describes how fishing industry income and fish population biomass vary with various fishery management strategies.

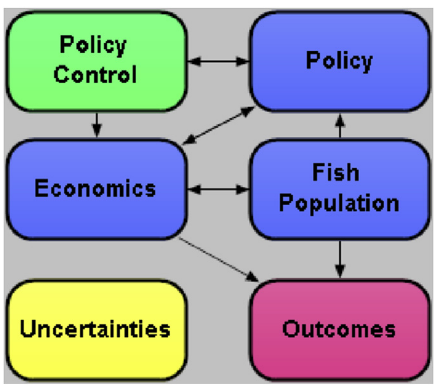


Fig. A1. Overall fisheries model structure in analytica software.

Based on Clark (2010) and discussions with fisheries experts, we use this simulation to evaluate four alternative regulatory instruments:

1. **Catch limit**: limits the number of fish (tonnage) allowed to be caught during each fishing season.
2. **Limited entry**: limits the number of fleets allowed to enter the fishery during each fishing season.
3. **Combination of catch limit and limited entry**: limits both the allowable catch and number of fleets during each fishing season.
4. **Individual quota**: total catch limit will be distributed to a limited number of fleets as individual catch quota. This strategy is an attempt to solve the common-property resource problem through privatization.

Table A1 displays the numeric values considered in the decision tool for the parameters that characterize each fishery management strategy, which includes the level for each regulatory instrument and the parameters that define any monitoring component. These values correspond to the verbal descriptions in Table 1.

Table A1
Parameter values used to define fishery management strategies.

User-defined variables	Available choices
Catch Limit Level	Low Limit (20,000) or High Limit (45,000)
Limited Entry Level	Low Entry (12 fleets) or High Entry (13 fleets)
Individual Quota Level	Low Quota (5,000) or High Quota (11,000)
Monitoring Level	Level 1 (185,000) or Level 2 (150,000)
Monitoring Frequency	1 year, every 5 years, or every 10 years
Adaptive Policy Level	Level 1 (small adjustment) or Level 2 (high adjustment)

The simulation's fish population component follows a dynamic resource-harvesting model (Clark, 2010) where fish population at time t is determined by the net natural growth rate of the population biomass and the harvest function. The net natural growth rate function[11] accounts for the population reproduction and natural mortality rate. The harvest function follows the Schaefer catch-effort relation (Schaefer, 1954), where harvest was determined by the catchability of the vessel (determined by different levels of fishing technologies), the effort level (number of vessels involved), and the fish population biomass.

The simulation treats fishing fleets as entities that they use various inputs such as fuel, gear and labor to catch fish and generate revenue. In the simulation's economic component, the daily profit equals total revenue minus the cost related to fishing effort. As shown in Equation (A1), annual revenue is given by the fish price multiplied by the daily number of harvest and the length of fishing season. The annual cost is given by the cost of fishing effort by the number of fleets fishing during the fishing season and the length of fishing season. If monitoring efforts are implemented, additional monitoring cost will also impact the annual profit level.

Equation A1: Annual fisher profit

$$\begin{aligned}\mathit{Annaul\ Profit}_t &= \mathit{Fish\ Price}*\mathit{Daily\ Harvest}_t*\mathit{Season\ Length}_t\\ &\quad - \mathit{Cost\ of\ Effort}_t*\mathit{Number\ of\ Fleet}_t*\mathit{Season\ Length}_t\\ &\quad - \mathit{Annual\ Monitoring\ Cost}\end{aligned}$$

The fishing cost is an increasing function of fishing effort but was set to zero if no effort was involved. To incorporate "effort creep" (Turris 2000)—a phenomenon where fishing companies will tend to switch to larger boats and larger gear when faced with limited entry management—we reduce the effort cost under limited entry, thus increasing the daily maximum effort level. In general, our model embeds the assumption that fishing companies will choose the fishing effort level that maximizes their daily revenue, as shown in Equation (A2).

Equation A2: Fishing efforts function

$$\mathit{Fishing\ effort}_t = \mathit{Fish\ Price}*\mathit{Catchability\ of\ Fleet}*\mathit{Pop}_{t-1}/2$$

Under catch limit and individual quota policy scenario, annual harvest will be determined by pre-determined harvest limit chosen by the users. The level of catch limit, individual quota and limited entry can also be adjusted if users decided to choose to monitor the fish population and implement adaptive policy. Annual profit function (Equation (A1)) would then incorporate the additional

[11] Dale Kiefer, USC, personal communication.

monitoring costs. Under open access, the fishing season is set to a constant. Under the various management scenarios, the fishing season may be shortened due to restrictions on allowable catch.

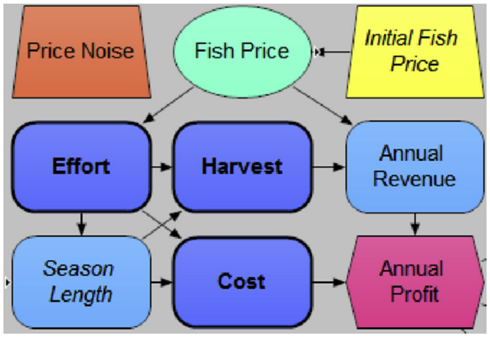


Fig. A2. Fishery economics module structure.

Fig. A2 shows the economic component, which assumes that the fishing industry chooses their annual fishing capacity commitments based on the price of fish, costs, biomass level, and the policies set by the regulatory agency. Both short-term (annual profit) and long-term (cumulative profit) economic outcome are evaluated.

Fig. A3 shows the population component, which captures the population growth dynamics mainly driven by fish reproduction, natural mortality, and fishing behavior (Equations (A2), (A3) and (A4)).[12] The model incorporates random shocks on reproduction (egg survival) rates. In addition, the model contains a fish population threshold which attempts to mimic the phenomenon of *depensation*: once the fish population goes below a certain threshold, in this frame, even a complete cessation of harvesting will not prevent extinction (Clark, 2010). In our model, such phenomenon is modeled by simply change the sign of natural growth at year t if previous year's fish population falls below the depensation threshold.

Equation A3: Fish population at time t

$$Pop_{\,t} = Pop_{t-1} + Natural\ Growth_t - Fish\ Loss_t$$

Equation A4: Natural growth at time t

$$Natural\,Growth_t = \begin{cases} Eggs\,Per\,Spawner * Survival\,Eggs\,Scalar * Pop_{t-1}^{Survival\ Eggs\ Expo} \\ \quad if\ \mathrm{Pop}_{t-1} \geq \mathrm{Depensation\ Threshold} \\ -Eggs\,Per\,Spawner * Survival\,Eggs\,Scalar * Pop_{t-1}^{Survival\ Eggs\ Expo} \\ \quad if\ \mathrm{Pop}_{t-1} < \mathrm{Depensation\ Threshold} \end{cases}$$

Equation A5: Survival eggs scalar function

$$Survival\ Eggs\ \ Scalar = Egg\ Survival\ Min + 10^{-6} * Egg\ Survival\ Rate$$

Equation A6: Fish loss function

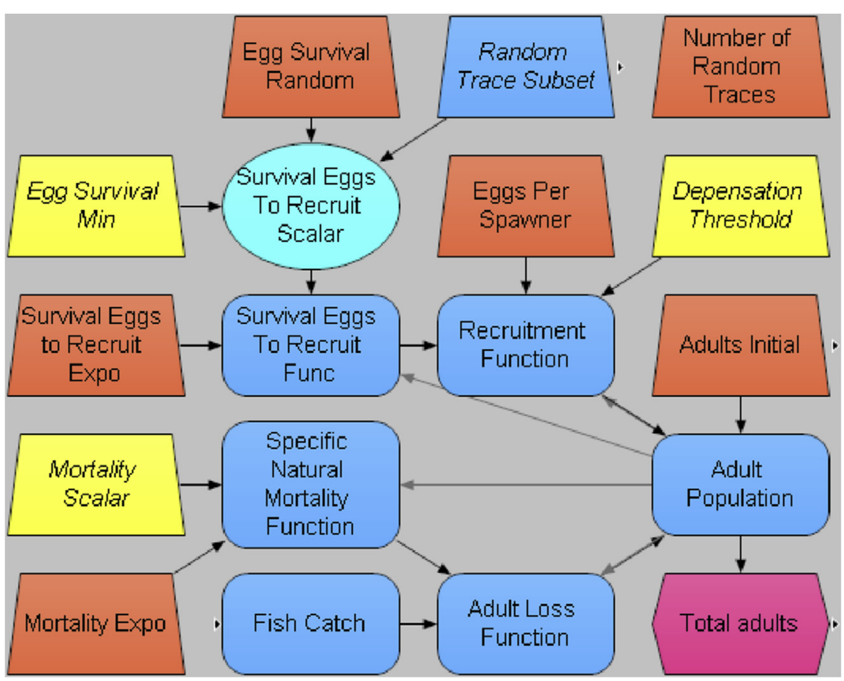


Fig. A3. Fishery population module structure.

$$Fish\ Loss_t = Annual\ Harvest_t + Mortality\ Scalar*\ Pop_{t-1}^{Mortality\ Expo}$$

[12] Dale Kiefer, USC, personal communication.

Fig. A4 shows the policy component. The user specifies one of the four regulatory instruments and an associated level of allowed catch, fleet, or quota. If the user also chooses to monitor and adjust, the policy module will monitor the fish population every 1, 5, or 10 time periods as specified by the user. If the level drops below the chosen threshold during one of the monitoring periods, the policy component adjusts the catch, fleet, or quota the user-specified, more stringent, level. If the fish population recovers during a subsequent monitoring period, the policy level returns to its original value.

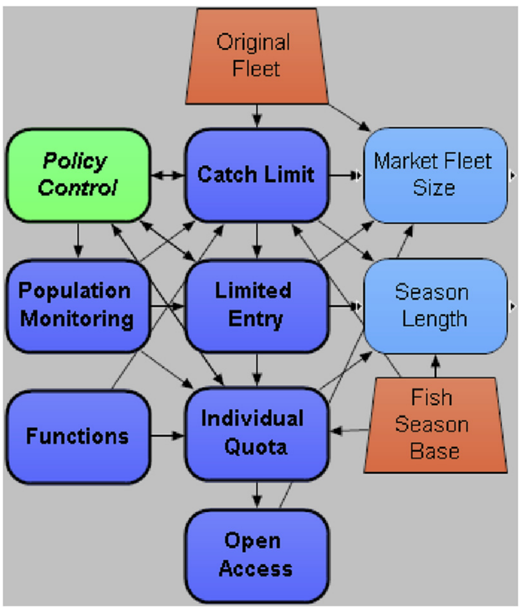


Fig. A4. Fishery management strategies module structure.

Generating the scenario and forecast conditions

The Scenario Condition includes three scenarios that lie at the vertices of the triangular region shown in Fig. 2. Table A2 lists the values for the uncertain model input parameters that correspond to these vertices. The column labeled "Fishing Technology" represents uncertainties affecting the catchability of fleet in Equation (A2). The column labeled "Fish Price" represents uncertainties affecting the economics of the fishery and refer to the parameters in Equation (A1). The columns labeled "Mortality Scalar," "Egg Survival Rate", and "Depensation Threshold" represent uncertainties affecting the fish population and refer to parameters in Equations (A4)–(A6), respectively.

To generate the probabilistic time series in Forecast Condition, we first generate a 2- point, space-filling distribution over the triangular region shown in Fig. 2, as shown in Table A2. This 21-point design includes the three scenarios and 18-points generated with a 36-point Latin-hypercube (LHC) design over the unit square, which is then pruned of all cases for which $x + y > 1$. We then place a probability distribution function over these points that is heavily peaked at one vertex and has only small weight for the other two vertices, so that there are appropriate tradeoff among the strategies. We chose the exponential distribution:

$$\rho(x_i, y_i) = \frac{e^{-\alpha[\lambda - \lambda y_i + (1-\lambda)x_i]}}{\sum_i e^{-\alpha[\lambda - \lambda y_i + (1-\lambda)x_i]}} \tag{1}$$

with the value of $\alpha = 1.3$ and of $\lambda = 4.5$. The last column of Table 2 shows the resulting probability weightings for the 21 futures. We can then calculate the mean, expected range, and extreme range performance of any strategy. We chose this probability distribution to generate the desired performance characteristics of the set of strategies. In particular, this distribution gives only a small number of strategies with both high expected value and non-zero fish populations at the 5th percentile.

Table A2
Twenty-one cases in experimental design.

X	Y	Fishing tech Int(3-2y)	Fish price (8+4y)	Mortality scalar (0.6 + 0.2x)	Egg survival rate (10^-6) (10-5x)	Depensation threshold (0.05 + 0.05x)	Probability
0.0	1.0	1	12	0.6	10	0.05	19.1%
0.0	0.0	3	6	0.6	10	0.05	0.8%
1.0	0.0	3	6	0.8	5	0.10	5.2%
0.0	0.9	1	11.29	0.61	9.78	0.052	9.3%
0.2	0.7	2	10.35	0.64	8.88	0.061	8.5%
0.1	0.7	2	10.03	0.62	9.46	0.055	4.8%
0.1	0.6	2	9.60	0.63	9.37	0.056	4.0%
0.3	0.5	2	9.26	0.65	8.74	0.063	4.6%
0.3	0.5	2	8.95	0.66	8.44	0.066	4.5%
0.5	0.4	2	8.69	0.69	7.66	0.073	5.9%
0.5	0.4	2	8.59	0.70	7.50	0.075	6.1%
0.2	0.4	2	8.16	0.64	9.06	0.059	2.3%
0.0	0.3	2	8.04	0.60	9.96	0.050	1.6%
0.3	0.3	2	7.82	0.66	8.61	0.064	2.4%
0.4	0.2	3	7.09	0.67	8.22	0.068	2.1%
0.1	0.2	3	6.95	0.61	9.64	0.054	1.2%
0.7	0.1	3	6.75	0.75	6.37	0.086	3.9%
0.8	0.1	3	6.64	0.75	6.15	0.089	4.1%
0.6	0.1	3	6.50	0.71	7.17	0.078	2.4%
0.9	0.0	3	6.29	0.78	5.47	0.095	4.8%
0.7	0.0	3	6.09	0.73	6.69	0.083	2.5%

Appendix B. Comparison of information scenario and forecast conditions

The experiment was designed so that the scenario and forecast conditions would present comparable information to users. The Scenario Condition has three scenarios that lie at the vertices of a triangular uncertainty space and laying an exponential probability distribution over that space generated the Forecast Condition. As shown in Fig. 2, the three scenarios – *Resilient Fishery and Economy*, *Vulnerable Fishery and Economy*, and *Resilient Fishery and Vulnerable Economy* – correspond to the 67th, 5th, and 33rd percentiles, respectively. This appendix compares the Pareto frontiers in each of the scenario/forecast pairs.

For example, the upper panel of Fig. B1 shows the 30-year profit and population for the best performing strategies in the *Resilient Fishery and Economy* Scenario. The lower panel shows the 30-year profit and population in the 67th percentile future, which as seen in Fig. 2, is close to the (0,1) vertex, that is, the scenario in the upper panel. With only one exception (Ind-L 10LH), the same strategies lie along the Pareto frontier in both panels and have the same ordering. The HighEV-R strategies lie interior to the Pareto frontier in both panels, though Ind-L 5HH is closer to it in the scenario panel. Note that the Pareto frontiers and the ordering of the strategies in both panels of Fig. B1 are similar to the ordering of the strategies by expected value in Fig. 2.

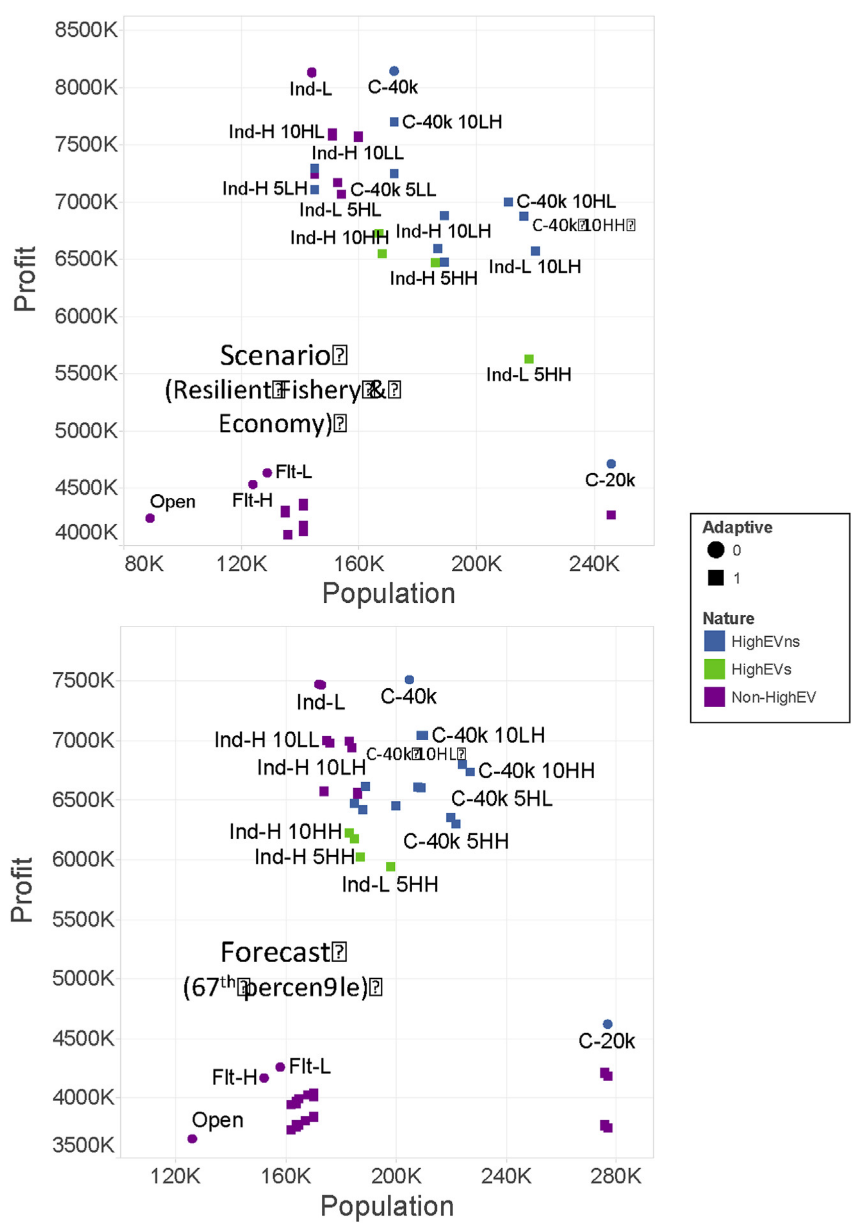


Fig. B1. Profit and population in optimistic futures from each condition.

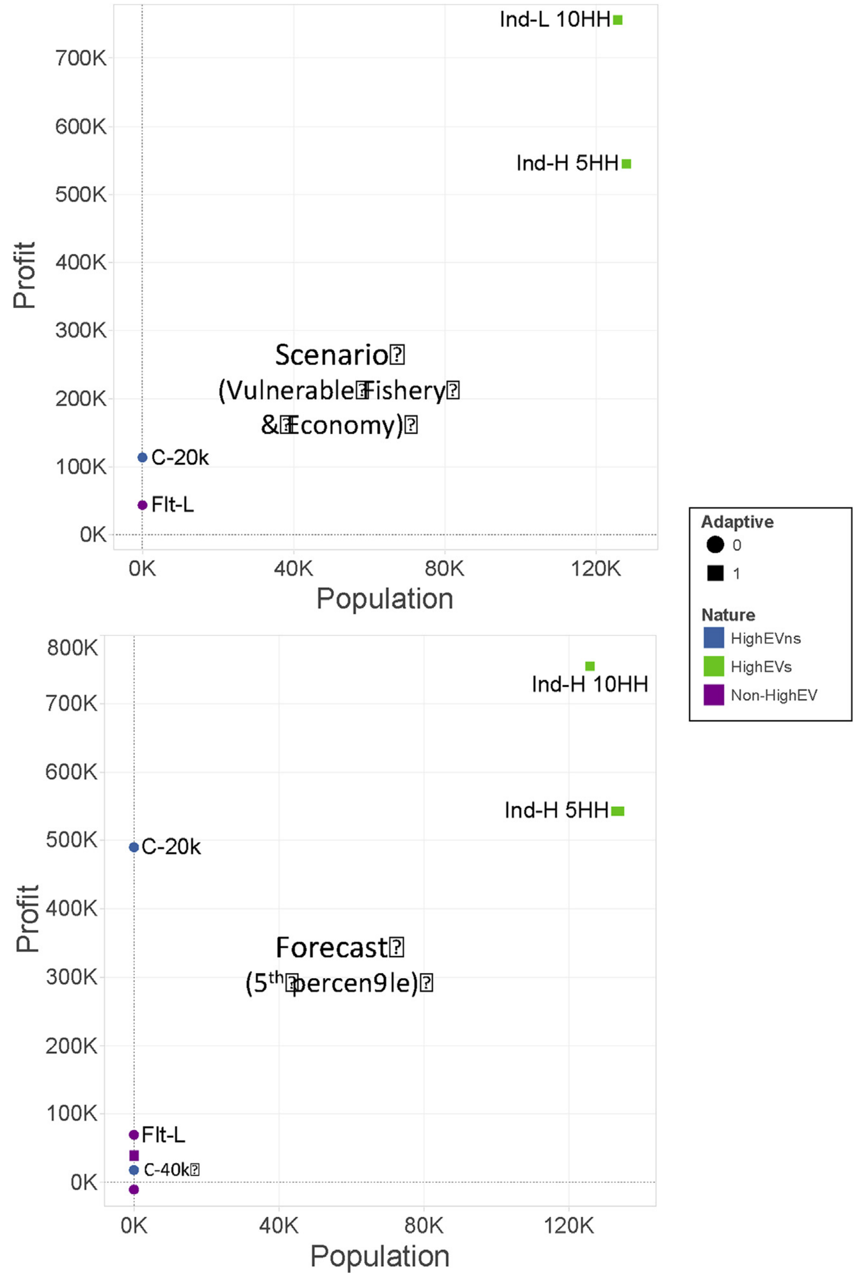


Fig. B2. Profit and population in worst case futures from each condition.

In another example, the *Vulnerable Fishery & Economy* scenario and 5th percentile future are also close in the uncertainty space, as shown in Fig. B2. The tradeoff curves for these two conditions are also nearly identical. In both, the Pareto frontier consists entirely of HighEV-S, which are the only strategies that do not drive the fish population to zero in these extreme futures. Most strategies also generate negative profits. In both conditions, C-20K has the highest (and positive) profits of any non-robust strategy. C-40Khas negative profits in the scenario condition and near zero, but positive, profits in the forecast condition.

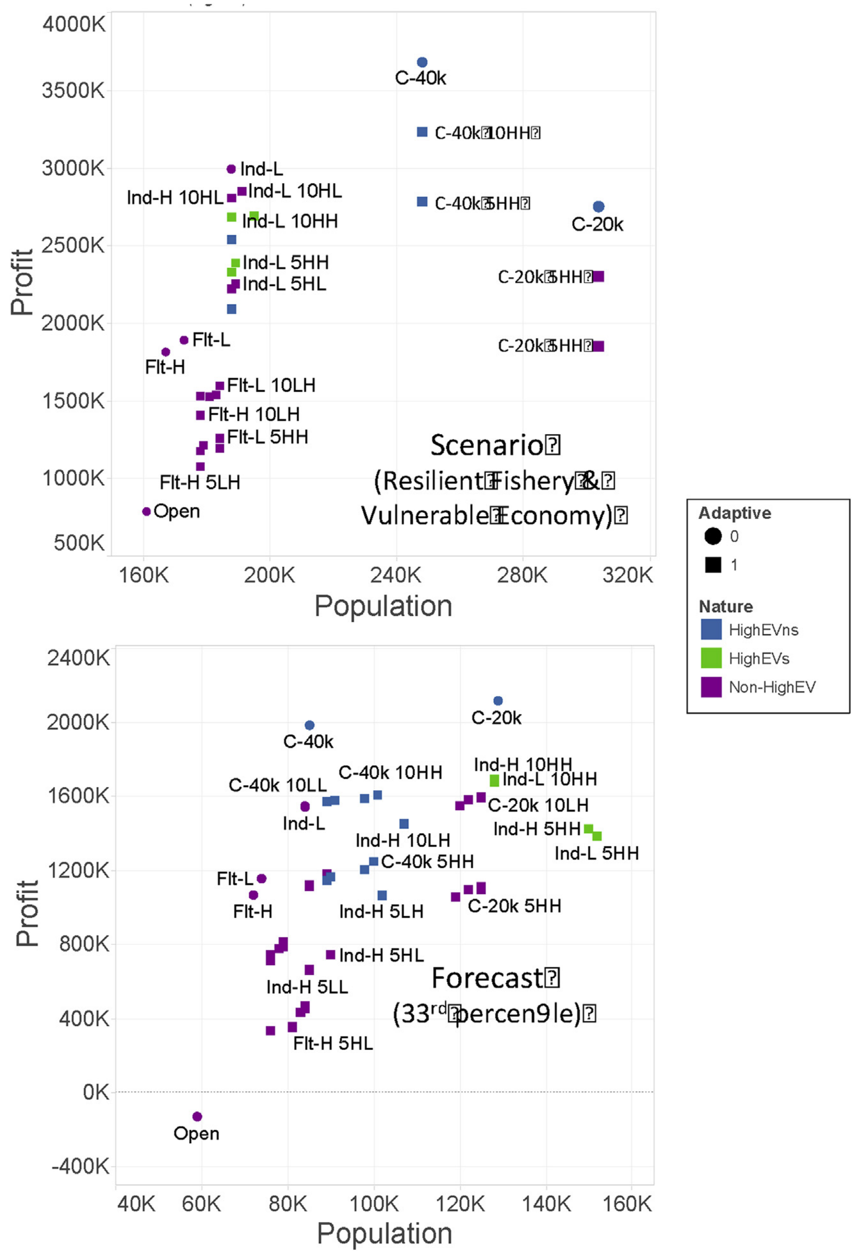


Fig. B3. Profit and population in pessimistic futures from each condition.

Fig. B3 also compares the *Resilient Fishery & Vulnerable Economy* scenario to the 33rd percentile future. These two futures are further apart in uncertainty space than the other two comparisons and the tradeoff curves are less similar. In the scenario condition, C-40Kand C-20K retain their place on Pareto frontier, with the HighEV-R strategies on the interior, while in the forecast condition C-20K and two of the HighEV-R strategies are on the Pareto frontier, with C-40Kon the interior. Note that HighEV-R strategies are further from the Pareto frontier in the Scenario rather than Forecast Condition, so that our test of the scenario hypothesis is conservative.

Appendix C. Post-experiment survey

After making the final choice, participants were directed to complete a questionnaire that included questions on (a) their experience with the decision tool, (b) self-reports on their decision process, (c) their evaluation of their group dynamics (in the dyad conditions only), (d) attitudes on environmental and free-market issues, and (d) demographics.

Specifically, respondents indicated their disagreement or agreement (using a 7-point Likert scale) to two questions having to do with visualizing the future during the task: “I tended to think about one vision of the future and planned with that future in mind” and “I tended to think about multiple possible futures and planned with all of those in mind.” Similarly, two questions asked about their focus on likelihood versus consequence during the task: “I focused on the likelihood of possible futures” and “I focused on the consequences of possible futures.” A separate question asked: “In general, how abstract or concrete did possible futures seem in this study?” with response options ranging from “very abstract” (=1) to “very concrete” (=7).

We used multiple sets of questions to measure group dynamics, including six that assessed willingness to find consensus or compromise, one on general satisfaction with the group, and seven on perceptions of the participants' dyadic partner (e.g., how pleasant and cooperative).

We used two existing attitude scales. The 15-item New Ecological Paradigm survey (Dunlap et al., 2000) assesses attitudes towards the environment and environmental impact (e.g., "We are approaching the limit of the number of people the Earth can support"). A second six-item test (Heath and Gifford, 2006) assessed attitudes towards the free market (e.g., "An economic system based on free markets unrestrained by government interference automatically works best to meet human needs").

Finally, demographic questions assessed gender, age, area of study, and educational attainment. A final question allowed respondents to leave comments on the experiment.

We used this survey to test two additional hypotheses regarding mechanisms by which scenario versus forecast presentation could influence how participants approach the choice problem. Among the differing, salient attributes of scenarios and forecasts, the former highlight multiple, distinct views of the futures while the latter highlight a single expected future with accompanying uncertainty and explicit statements of likelihood. Therefore, we predict that:

H5. Participants in the Scenario Condition, compared to those in the Forecast Condition, will be more likely to visualize multiple futures, less likely to visualize a single future, less likely to focus on likelihood, more likely to focus on consequences, and more likely to see the possible futures as concrete.

Consistent with the arguments for H4, we also expect that:

H6. Dyad participants in the Scenario Condition will perceive greater emphasis on consensus and compromise than with dyad participants in the Forecast Condition. We also expect that this will result in greater satisfaction with group dynamics and a more positive view of their dyad partner.

The post-experiment questionnaire provides additional insight to potential mechanisms for how scenarios versus forecasts affect decision structuring and choice. H5 suggested that those in the Scenario Condition would be more likely to visualize multiple futures, rather than a single future. The first two rows of Table C1 below show that those in the Scenario Condition were significantly less likely to visualize a single future and nonsignificantly more likely to visualize multiple futures, largely supporting H5. These two responses were strongly and negatively correlated ($r = -0.43$, $p < 0.001$), and a composite measure of the two also significantly differed across the two conditions (Mann-Whitney $Z = -2.46$, $p = 0.01$). The resulting composite supports this hypothesis.[13]

H5 also stated that those in the Scenario Condition would focus less on likelihood and more on consequences than would those in the Forecast Condition. Hence, we similarly compared participant responses in the two conditions to questions asking how much participants focused on these two types of information. As shown in Table C1, those in the Scenario Condition were indeed less likely say that they focused on likelihood than were those in the Forecast Condition, and also more likely to say that they focused on consequences. Neither difference, however, reached significance.

To test whether scenarios would feel more concrete and forecasts more abstract, we compared participant responses in the two conditions to a question that asked "In general, how abstract or concrete did possible futures seem in this study?" Response options ranged from "very abstract" (=1) to "very concrete" (=7). Contrary to this hypothesis, those in the Scenario Condition reported that the futures were slightly less concrete (and more abstract), but the difference was only marginally significant ($p = 0.054$).

Table C1
Post-experiment survey responses by experimental condition.

Self-reported decision processes	Forecast condition Mean (SD)	Scenario condition Mean (SD)	Mann-Whitney Z-statistic
Visualize one vision of future	4.46 (1.43)	3.97 (1.63)	−3.30***
Visualize multiple futures	4.73 (1.41)	4.88 (1.46)	−1.38
Focus on likelihood	4.91 (1.35)	4.75 (1.51)	−0.77
Focus on consequence	5.52 (1.24)	5.67 (1.09)	−1.02
Abstract vs. concrete	4.66 (1.31)	4.45 (1.25)	−1.93

* Two-sided $p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Finally, H6 states that scenarios help promote consensus and compromise with decision-making groups (and result in a generally better group experience). To test this hypothesis (relevant only to the dyad condition) we considered six questions on group conflict, consensus, compromise, and perceived flexibility; a general question on satisfaction with the group decision-making process; and seven questions rating their dyad partners (e.g., on pleasantness and cooperativeness). Across all fourteen responses, none of the responses differed across conditions.

The post-experiment survey included the following questions:

1. In general, how easy was it to use the computer tool? (1 = very difficult, …, 7 = very easy)
2. In general, how satisfied are you with your final decision? (1 = not satisfied at all, …, 7 = extremely satisfied)
3. In general, how abstract or concrete did possible futures seem in this study? (1 = very abstract, …, 7 = very concrete)
4. When reading each of the following statements, please indicate how much you agree with that statement. When thinking about the fishery strategy … (1 = strongly disagree, …, 7 = strongly agree)
   - I tended to think about one vision of the future and planned with that future in mind.
   - I tended to think about multiple possible futures and planned with all of those in mind.
   - I focused on the likelihood of possible futures.
   - I focused on the consequences of possible futures.

The following questions were asked only of those participants in the group conditions.

[13] We also ran these tests as ordered logistic regressions, controlling for individuals versus dyads and for lab space. Results were qualitatively similar.

5. When reading each of the following statements, please indicate how much you agree with that statement. When thinking about the fishery strategy … (1 = strongly disagree, …, 7 = strongly agree)
   - It felt like there was conflict within the group.
   - I felt a strong need for the group to reach consensus.
   - The group generally sought to find consensus.
   - I felt a strong need to compromise with the other group member.
   - The group was generally willing to compromise.
   - The group sought out flexible solutions.
6. In general, how satisfied were you with the group decision-making process? (1 = not satisfied at all, …, 7 = extremely satisfied)
7. For the following questions on this page, please indicate how you would describe the other person in your group.
   - 1 = very rude, …, 7 = very pleasant
   - 1 = very difficult to work with, …, 7 = very cooperative
   - 1 = very unintelligent, …, 7 = very intelligent
   - 1 = very inconsiderate, …, 7 = very considerate
   - 1 = very opinionated, …, 7 = very willing to compromise
   - 1 = very socially awkward, …, 7 = very socially comfortable
   - 1 = very lazy, …, 7 = very hard working
8. How much would you say you identified with the role of the environmentalist? (1 = not at all, …, 7 = very strongly)
9. How much would you say you identified with the role of the fisherman? (1 = not at all, …, 7 = very strongly)
10. How much would you say your partner represented the interests of the fishermen? (1 = not at all, …, 7 = very strongly)
11. How much would you say your partner represented the interests of the environmentalists? (1 = not at all, …, 7 = very strongly)

The following questions were asked only of those participants in the scenario conditions.

Consider each of the scenarios that you saw in the computer tool. For each, please answer the following questions.

12. Scenario 1: Strong fishery, strong economy
    - How credible was this scenario as a characterization of a possible future? (1 = not credible at all, …, 7 = extremely credible)
    - How important was this scenario for a planning process? (1 = not important at all, …, 7 = extremely important)
    - How likely was this scenario, in your mind? (1 = not likely at all, …, 7 = extremely likely)
13. Scenario 2: Strong fishery, weak economy
    - How credible was this scenario as a characterization of a possible future? (1 = not credible at all, …, 7 = extremely credible)
    - How important was this scenario for a planning process? (1 = not important at all, …, 7 = extremely important)
    - How likely was this scenario, in your mind? (1 = not likely at all, …, 7 = extremely likely)
14. Scenario 3: Weak fishery, weak economy
    - How credible was this scenario as a characterization of a possible future? (1 = not credible at all, …, 7 = extremely credible)
    - How important was this scenario for a planning process? (1 = not important at all, …, 7 = extremely important)
    - How likely was this scenario, in your mind? (1 = not likely at all, …, 7 = extremely likely)

The following questions were asked only of those participants in the forecast conditions.

Consider the forecast that you saw in the computer tool, in terms of the fish population and economy. For each, please answer the following questions.

15. How credible was the forecast as a characterization of a possible future? 1 = not credible at all, …, 7 = extremely credible)
16. How important was the forecast for a planning process? (1 = not important at all, …, 7 = extremely important)

In addition, all participants presented the questions from Dunlap et al.'s (2000) 15-item New Ecological Paradigm survey and from the 6-item survey by Heath and Gifford (2006) to assess attitudes towards markets. All participants were also asked the following demographic questions:

17. Please indicate your gender: Male, Female, Other
18. What is your age? 18–27, 28–37, 38–47, 48–57, 58–67, 68+
19. What is the major of the degree you are currently pursuing, or most recently finished?
20. What is the highest level of education you've completed? Some schooling, but no diploma or degree, High school diploma or GED, Some college, 4-year college degree, Master's degree, PhD degree
21. Please leave any comments you have about the experiment here.

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