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When Experience Is Better Than Description: Time Delays and Complexity

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ABSTRACT

The dominant sampling paradigm of experience-based choice is extended by exploring two realistic aspects of decisions. First, frequency judgments were studied in situations involving a delay between information acquisition and judgment. This time gap undermines recall from working memory and favors the natural human capacity to encode frequencies effortlessly. Deferred judgments from experience were found to be more accurate than judgments from description, both for absolute and rank-order judgments. Second, task complexity was varied. This showed that—as decision tasks become more complex—participants are willing to trade-off detailed but complex descriptive information for less accurate but simpler information sampled from experience. Moreover, there were no individual differences due to numerical/rational abilities. Results from the two studies suggest that information obtained from experience can be more valuable than descriptive information in that it can both lead to better frequency judgments in deferred tasks and simplify cognitive representations of complex choice tasks. Copyright © 2009 John Wiley & Sons, Ltd.

KEY WORDS decisions from experience; frequency judgments; individual differences; preference for experience

Recent findings show that choices based on descriptive information are different from choices based on experience (Hertwig, Barron, Weber, & Erev, 2004; Weber, Shafir, & Blais, 2004). This difference has been studied by contrasting the traditional design of choice between lotteries, where the outcomes and probabilities of lotteries are explicitly described to participants, to a new experimental design that simulates experience experimentally. In this recent paradigm, participants also choose between lotteries but instead of obtaining explicit descriptions of them, they have to infer outcomes and probabilities by sampling.

Though in the sampling paradigm participants are urged to sample as much as desired, research reveals that samples gathered from experience tend to be limited and misrepresentative of underlying probabilistic processes thereby leading to the underweighting of rare events in choice. Even when samples from experience are large and representative, more recent events tend to receive more weight than less recent ones, biasing decisions (Hertwig et al., 2004). Moreover, evidence suggests that, under specific experimental

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conditions, underweighting of rare events in decisions from experience undermines maximizing behavior (Erev & Barron, 2005). Other studies have shown that experience can lead to highly risky behavior, as when we learn to stop using safety devices (Yechiam, Erev, & Barron, 2006); undermine warnings (Barron, Leider, & Stack, 2008); and expose ourselves to rare but deadly terrorist attacks (Yechiam, Barron, & Erev, 2005).

A recent study by Hertwig and Pleskac (2008) shows that samples from experience, though small and biased, amplify differences between two prospects simplifying the choice between them. This finding suggests that, in contrast to what has been observed to date, in certain contexts experience can be helpful in the decision process.

In the sampling paradigm, experience is collected by clicking on buttons that draw random outcomes from an underlying probability distribution. This process is done immediately before choosing between two options, typically a two-outcome lottery and a certain payoff. Versions of this experimental design include: No-cost sampling followed by a one-shot choice, forced no-cost sampling followed by a one-shot choice, repeated choices with feedback, repeated choices with feedback about foregone payoffs, and other variations (see e.g., Barron & Erev, 2003; Hertwig et al., 2004; Hau, Pleskac, Kiefer, & Hertwig, 2008; Newell & Rakow, 2007; Rakow, Demes, & Newell, 2008). In all versions, sampling is followed by immediate choice. Although this simplification has led to valuable insight about experience-based choice, there are still questions about its generality.

This study examines two extensions to the no-cost sampling paradigm that highlight additional positive aspects of experience. In Experiment 1, I study whether the natural human capacity to encode past frequencies of events favors experience over description as a source of information in an inference task. While Experiment 1 explores the quality of information obtained from experience relative to that obtained from description, Experiment 2 extends this notion to contexts of increasing complexity. Specifically, I study decision makers' preference for information from experience as a function of task complexity, controlling for individual differences in rationality and numeracy.

DEFERRED FREQUENCY JUDGMENTS

One way in which the sampling paradigm deviates from most decisions made outside the laboratory is that information from experience is obtained immediately before choice. In naturalistic settings, however, experience in relation to risky events is likely to be collected over longer periods. People smoke for years; invest for years; and purchase goods and services over a lifetime. As a result, choices from experience may not be restricted to information stored in working memory, as forced experimentally in the sampling paradigm, but to information stored in longer-term memory. Moreover, whereas working memory has been shown to be limited to seven (Miller, 1956) or even four (Cowan, 2000) units of information, long-term frequency judgments have shown to be surprisingly accurate (Zacks & Hasher, 2002). Indeed, researchers have tested the human capacity to encode frequency information automatically and effortlessly with various items, such as words, pictures, sentences and even the "gist" of sentences (Gude & Zechmeister, 1975), both experimentally and in naturally occurring environments.

Models of decision making based on learning have addressed the issue of memory burden in choices from experience. For example, associative learning models like the value-updating model (Hertwig, Barron, Weber, & Erev, 2006) and the fractional-adjustment model (March, 1996) focus only on the latest outcome experienced by the decision maker, minimizing memory load. In these models, the attractiveness of an option is shaped sequentially with every outcome observed. Thus, decision makers need only recall the attractiveness of the option, not the sequence of outcomes sampled. Decision makers then choose according to their inclination toward one option over the other, rather than on objective processing of choice information.

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The role played by the attractiveness of options is unclear in frequency judgment tasks, where the response mode is not choice but explicit frequency estimates. While it is expected that detailed information will lead to better informed decisions and better inferences than samples from experience, this assertion may not hold in all contexts and situations. In the long term detailed information from description may be difficult to recall, especially in a complex context. In such situations, the human capacity to recall accurately repeated samples of events may lead to more accurate inferences than those based on detailed descriptive information.

EXPERIMENT 1

This experiment tests the hypothesis that frequencies obtained from experience lead to better deferred judgments of frequency than probabilities obtained from description. One distinction of Experiment 1 from previous studies of experience-based choice is that the dependent measure used is not choice but judgments of frequency. While choices involve the elicitation of preferences between options, judgments of frequency involve inferences about future outcomes. This distinction has implications for the claims that small samples lead to biased probability estimates that influence choice away from what would be expected from description (Fox & Hadar, 2006).

Additionally, Experiment 1 is distinctive because it includes a delay between information acquisition and frequency judgment. This delay promotes judgments of frequency that are not based on working memory but on longer-term memory, thereby, reflecting a realistic feature of human judgment. Finally, while most work on experience-based choice has focused on choices between two options, which involve the evaluation of two probabilistic events, Experiment 1 involves a more complex context with four probabilistic events to be evaluated.

Materials, methods, and procedures

The experiment was run in a computerized laboratory. Participants were 102 undergraduate students from various backgrounds at Universitat Pompeu Fabra, Spain. They were randomly assigned to two between-subject conditions: Description, with 48 participants, and experience, with 54 participants. The experiment involved the following three stages: Information acquisition; cognitive depletion; and response.

Stage 1: Information acquisition

In Stage 1, participants in both experimental conditions read the following question ‘‘In which of the following four cities does it rain most often?’’ To answer the question, participants obtained information about the incidence of rain in four cities. The form of their information depended on the subjects’ conditions. In the description condition, participants saw a descriptive table on the computer screen that displayed the probabilities of rain for each of the four cities to be evaluated. The header of the table read ‘‘Probability of rain for any day of the year.’’ Entries in the table for each city displayed a probability of rain between 0 and 1.

The experience condition differed from the description condition in that, instead of observing the probabilities of rain displayed on the screen, participants had to infer them by clicking on buttons exactly as in the no-cost sampling paradigm. Participants saw four buttons on the screen labeled with the names of the same cities displayed in the description condition. Clicking on one of the four buttons simulated a day in the indicated city. Each click elicited a random draw from a probability distribution. Probabilities were the same as those observed by participants in the description condition. Outcomes from each draw were either ‘‘sun’’ or ‘‘rain,’’ and were displayed both in text and a picture ($3 \times 3\,\mathrm{cm}^2$) of a shining sun or a raining cloud. The pictures and text appeared above each of the corresponding buttons. Participants were instructed that they could sample in whatever order they desired and for as long as liked.

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On the same screen where participants saw the probabilities of rain (description) and sampled the cities (experience), four buttons were displayed and labeled with the names of the corresponding cities. After participants had observed the probabilities of rain (description) and sampled the cities sufficiently (experience) they provided their answer to the question (in which of the following four cities does it rain most often?) by clicking on one of the four buttons. This recorded their answer and automatically took them to Stage 2.

City names were fake and foreign-sounding to Spanish participants: Harford (H), Kent (K), Talbot (T), and Somerset (S). The order in which the cities appeared on the screen, in both conditions, varied between subjects as in a Latin square: HKTS, SHKT, TSHK, and KTSH.

Stage 2: Cognitive depletion

This stage was designed to draw attention away from the initially observed data. It did not differ between conditions. Participants completed two tasks, a logic-based number puzzle followed by a reading task. After spending 20 minutes in the completion of the puzzle, participants moved to a different screen regardless of whether they had completed the game. In the following screen, participants read a philosophy text of 1049 words. Before reading, they were instructed that they would have to answer seven questions about the text. The questions induced memory effort.

Stage 3: Response

Stage 3 did not differ between conditions. Based on the information obtained in Stage 1, participants read and answered the following question: ‘‘How many days do you estimate that it will rain in a ten-day period in each of the four cities?’’ Participants filled out a box below the name of each city with their answer. The display on the screen was identical to Stage 1 except that instead of a table of probabilities (in the description condition) or buttons (in the experience condition) participants saw four empty boxes to type in their estimates of days of rain. After filling the four boxes they clicked on a button labeled ‘‘continue’’ located at the bottom of the screen that led to the end of the experiment.

Compensation

Participants read the compensation scheme specific to each stage before starting the task at each stage. The compensation scheme was the same for both conditions, and was designed to elicit accurate judgments of frequency. Participants were paid 2€ for showing up. In Stage 1, they were paid 1€ for the correct answer. In Stage 2, they were paid 0.10€ for each of 81 cells of the number-puzzle filled correctly and 1€ for each correct question in the text task. In Stage 3, they were paid for the accuracy of their frequency estimates. Perfect accuracy of estimates was compensated with 3€ while each 0.1 deviation in the estimated probability reduced the compensation by 0.1€ (e.g., a 0.20 error was compensated with 3€−0.20€ = 2.80€). Rank-order accuracy was compensated with 0.10€ for each correct binary relation between city. The average payment was 12.5€.

RESULTS OF EXPERIMENT 1

One participant was removed from the description condition for not following laboratory procedures. Seven participants were removed from the experience condition. One of these provided four, not one, cities as an answer to question 1. The other 6 participants were removed for failing to draw samples from at least one city, revealing either a lack of interest in the experiment or a misunderstanding of the instructions. The answers of

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the participants removed were analyzed and suggest random answers. The mean absolute distance of their judgments (translated into probabilities) from 0.5, which represents the safest answer without information, amounted to 0.15, whereas the mean absolute difference of the rest of participants was 0.25. The final sample of participants consisted of 47 in the description condition and 47 in the experience condition.

Samples in the experience condition were uniformly distributed across cities. The mean sample size amounted to 18 draws per city (SD = 15.6); 72 draws per problem. Observed samples were rank-ordered with respect to the observed probability of rain in each city; and observed rankings were individually examined against the objective ranking of cities with respect to probability of rain. The median rank correlation coefficient (Kendall's tau-a) was $\tau = 1$.

In Stage 1, only four participants in the description condition and six in the experience condition failed to identify the most rainy city.

In Stage 3, mean frequency judgments, for the four cities, were more accurate in experience than in description (Table 1). Judged frequencies of rain were converted to probabilities to be comparable with objective probabilities. The difference between conditions was significant in Somerset and Harford. In Talbot, which participants had to identify as the most rainy city, judgments were highly accurate in both conditions. The aggregate judgment error, calculated as the sum of absolute values of the differences between objective probability and judged frequency (translated to probabilities), was higher in description (0.74) than in experience (0.61). A multivariate repeated-measures ANOVA shows a significant between-subject effect ($F(4,89) = 2.83$, $p = .029$) for the difference between judgments from description and experience.

Another quality dimension of judgments is their variance. While noisy samples could be expected to lead to judgments with higher variance than judgments elicited from precise probabilities, the opposite was observed. Frequency judgments from description showed a slightly higher variance than those from experience. This difference, though not statistically significant, is present in the four cities. Moreover, the direction of the errors is of interest. Errors toward 0.5 reveal more conservative judgments given the current compensation scheme. As expected, in both conditions and across cities, average judgment errors were toward 0.5. This effect was emphasized in Talbot and Harford, where the event involved a small probability of occurrence (0.1 of sun and 0.1 of rain, respectively). Overestimation of low probabilities and underestimation of high probabilities were also found by Attneave (1953) and Erev and Wallsten (1993) in the context of frequency and probability inferences, respectively. The regression toward the mean is motivated by the compensation scheme. The finding, however, is that across cities, this effect was statistically more pronounced in judgments from description than in those from experience.

Table 1. Judgments from experience and description

		Kent	Talbot	Somerset	Harford
Objective probability		0.30	0.90	0.60	0.10
Mean observed probability	Description	0.30	0.90	0.60	0.10
	Experience	0.29	0.91	0.61	0.09
	SD	0.17	0.08	0.14	0.09
Mean frequency judgments	Description	0.38	0.80	0.43	0.34
	SD	0.24	0.20	0.25	0.22
	Experience	0.32	0.81	0.57	0.26
	SD	0.18	0.16	0.22	0.18
p-value for different means		.205	.733	.005	.059
p-value for different variances		.155	.203	.869	.352

Note: Frequency judgments were reported by participants as ''number of days'' but these were converted to probabilities for an easier comparison. Mean observed probability is calculated as the observed probability of rain averaged across subjects. *p*-values correspond to two-tailed *t*-tests for samples with different variances.

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Did larger samples lead to more accurate frequency judgments? Results were fitted to a linear model in which aggregate judgment error is explained by the log of total sampling in the four cities. The OLS-estimated parameter $\beta = -0.15$ ($t(46) = -2.12$, $p = .040$) suggests a negative relationship between sampling and judgment error, as might be expected. Moreover, judgments from subjects whose samples were close (± 0.05) to the expected probability were more accurate than those whose samples were more distant (mean judgment error of .12 vs. .17). The difference between mean judgment errors is statistically significant ($t(186) = -2.11$, $p = .035$, two-tailed).

Rank-order judgments

Naturally occurring frequencies tend to be coded in memory even when there is no precise goal specified and therefore no intention (Hasher & Zachs, 1979, 1984). Experiment 1 provides additional evidence of this adaptive capacity. Moreover, this capacity favors experience over description as a source of information for deferred frequency judgments. The analysis of frequency judgments for less rainy cities, a task that was not specified in the stage of information acquisition, reveals a better performance of judgments from experience. The rank correlation between the objective ranking of cities, according to their probability of rain, and the judged ranking was assessed individually for each participant. The median rank correlation coefficient (Kendall's tau-a) in the experience condition was $\tau = 0.83$ and $\tau = 0.67$ in the description condition. Notably, the median coefficient between the judged rankings and the observed rankings in the experience condition was also $\tau = 0.83$.

In summary, deferred frequency judgments from experience were more accurate than those from description on three measures. Judgments of frequency from experience showed less absolute mean error, less variance, and less ranking error than judgments of frequency from description.

DISCUSSION OF EXPERIMENT 1

In the description condition, participants need only compare probabilities to find the correct answer, and therefore, do not incur much effort or spend much time involved with the problem. In the experience condition, participants need to invest effort exploring the possible outcomes in the cities, resulting in a higher involvement with the problem. The amount of time and effort involved in each condition reflects a realistic aspect of the experience-description duality. Additionally, in the learning process, participants in the experience condition gathered information that was not central to the question being asked, but that became valuable in a future context.

Even though participants in the description condition were explicitly provided with detailed information to provide their answer, they were outperformed by participants in the experience condition who had to infer the answer from limited samples. Fox and Hadar (2006) also find highly accurate probability judgments from experienced frequencies when elicited immediately after experience. However, these authors claim that small samples, and the inaccurate probability estimates obtained from them, account for the deviations observed in the choice pattern from experience relative to description. Results from Experiment 1 suggest that when frequency judgments are delayed, even when samples are small, likelihood estimates are highly accurate relative to objective probabilities.

While participants in the experience condition had to translate from observed frequencies to relative frequencies (X out of 10), participants in the description condition had to translate from probabilities to relative frequencies. Is the translation from probabilities to relative frequencies driving the pattern of results? In Stage 3, 79% of the participants in the description condition stated the correct relative frequency of the most rainy city, suggesting that the translation from probabilities to relative frequencies was not an obstacle. In the remaining cities, this proportion drops to 28% (Kent), 36% (Somerset), and 21% (Harford). Moreover,

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in rank-order judgments, where the difference between conditions is most marked, translation from probabilities to relative frequencies should play less of a role, given that participants were able to compare between cities that displayed rain information in constant units.

Results from Experiment 1 are especially relevant provided that probabilities, instead of frequencies, are the format chosen to describe problems in studies of choice where experience is contrasted with description (Barron & Erev, 2003; Erev, Glozman & Hertwig, 2008; Hertwig et al., 2004; an exception is Rakow et al., 2008, who include a description condition with described frequency information).

TASKS OF DIFFERENT COMPLEXITY

Experiment 1 studied frequency judgments in a context with four probabilistic events. This context is more complex than previous studies where decision makers choose from two options where, commonly, one probabilistic outcome is compared to a certain payoff. Results from Experiment 1 suggest that, in this more complex environment, even when samples are small and judgments are made after a delay, experience can lead to accurate judgments of frequency. The relevance of detailed descriptive probability information was thus questioned. Experiment 2 described below extends the investigation of the value of experience as a simplifying mechanism in complex environments.

In simple contexts where information is easily understood and processed, as in the problems in prospect theory (Kahneman & Tversky, 1979), people would be expected to rely on description. In fact, preliminary findings suggest that in this simple context, when both information from description and experience are available simultaneously, and when participants can sample as much as they want, they rely predominantly on description (Lejarraga, 2006). Though in a different design, however, recent findings point in the opposite direction. When samples from repeated choices are forced to be large, repetitive favorable outcomes from experience undermine descriptive warnings (Barron et al., 2008).

Certain decision situations are intricate even in the face of detailed descriptive information, and complete but complex descriptive information can induce costly analytic effort. Consider Hertwig et al.'s (2004) medical example in which a doctor evaluates the decision to operate on a patient. The doctor knows that the success of the surgery depends on two (for simplicity) independent events: The accuracy of the diagnosis and the precision of the surgery. From his scientific readings, the doctor is not only aware of the probabilities of the two individual events but also has the experience of having gone through that surgery successfully every time he has done it. The doctor experiences the surgery as a binary event: It can either be successful or not. In this type of scenario, considering all possible outcomes and joint probabilities involves costly cognitive effort that the decision maker may prefer to avoid in the face of experience. In this context, experience appears as a simplified source of information, and payoff frequencies derived from sampling may be easier to interpret than complex probability information. In addition to more simple information, experience can involve an emotional component that may provide a feeling, a ''hunch,'' of what options entail (Bechara, Damasio, Damasio & Anderson, 1994) which is absent in descriptive information.

Payne, Bettman, and Johnson (1993) studied extensively the trade-off between effort and accuracy, particularly in the domains of multi-attribute choice. Their findings indicate that decision-makers economize on effort while attempting accuracy. People have several decision strategies that range from costly but precise weighted-averages to simple but less accurate heuristics. In general, as decisions become more complex people tend to switch strategies toward simplifying heuristics. Experiment 2 explores whether this tendency to search for simplifying mechanisms in complex scenarios extends to the choice of experience over description as a source of information. It tests whether experience is preferred over description as a simplifying source of information depending on the complexity of the decision situation. The main implication of this hypothesis is that overweighting of rare events derived from description (Kahneman &

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Tversky, 1979) and underweighting of rare events observed in experience (Hertwig et al., 2004), are also situation-dependent.

An additional aspect that may influence the preference for experience or description is the set of individual characteristics of decision makers. If dealing with complex descriptive information entails costly cognitive effort, individual differences could be important. Specifically, participants with low ability in rational processing should prefer experience over description more often than participants with high ability on this dimension.

While there is evidence that individual personality differences with respect to rational thinking influence decisions (Stanovich & West, 1998), there is no knowledge on the influence of individual differences on the preference for experience. Yet, preliminary results suggest that participants classified as having high rational ability draw larger samples from lotteries than participants with low rational ability (Lejarraga, 2006). This difference in the willingness to search for additional information can influence the preference of experience over description.

EXPERIMENT 2

This experiment tests the hypothesis that experience offers a simplified view of complex decision situations. If lottery complexity involves costly analytic effort, participants are expected to reveal an increasing preference for experience over description as lotteries become more complex. The experiment also provides insight into the following questions: Do people still underweight rare events when intentionally deciding from experience? Do measures of rational ability, rational engagement, and numeracy explain the preference for experience over description?

Materials, methods, and procedures

The experiment was run in a computerized laboratory. Participants were 124 undergraduate students from various backgrounds at Universitat Pompeu Fabra, Spain. They were randomly assigned to one of three between-subject conditions: *Simple* (38 participants), *medium* (41 participants), and *complex* (39 participants). Participants were presented with seven decision problems (see Table 2) in which they had to

Table 2. Percentage A-choices in experience and description

Decision problem			% of A-choices				% correct predictions	
No.	A	B	Experience	Description	Difference		FAM for experience	CPT for description
1	4€, 0.8	3.5€	29	21	8	($N_e = 45$, $z = 1.03$, $p = .300$)	80	79
2	−3.5€	−4€, 0.8	49	24	25	($N_e = 47$, $z = 2.80$, $p = .004$)	44	76
3	3€, 0.9	2.8€	45	27	18	($N_e = 44$, $z = 2.04$, $p = .040$)	46	73
4	2€, 0.9	3€, 0.6	36	84	−48	($N_e = 45$, $z = 5.31$, $p < .001$)	39	84
5	−3€, 0.6	−2€, 0.9	51	64	−13	($N_e = 45$, $z = 1.42$, $p = .153$)	75	64
6	5€, 0.4	4€, 0.5	13	60	−47	($N_e = 40$, $z = 4.94$, $p < .001$)	55	60
7	−5€, 0.4	−4€, 0.5	37	45	−8	($N_e = 52$, $z = 0.97$, $p = .329$)	63	45

Note: Problems are expressed in the following manner: Payoff, probability. The probability is omitted for certain payoffs. In all lotteries, the non-stated outcome is 0 with the complementary probability. Ne: Number of participants choosing from experience. 118-Ne is the number of participants choosing from description. The difference between A-choices is a two-tailed z-test for proportions. Predictions by cumulative prospect theory (CPT) are based on outcomes and probabilities of gambles, whereas predictions by the fractional-adjustment model (FAM) are based on observed samples.

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choose between two lotteries labeled A and B. The order of appearance of problems was randomized between subjects.

The format in which the problems were presented varied across conditions. Formats were designed to create increasing complexity in the decision context (as shown in Figure 1). In the *simple* condition, lotteries involved one random event; in the *medium*, lotteries involved two stages of random events; and in the *complex*, lotteries involved three stages of random events. Problems were objectively equivalent across conditions: Payoffs were equivalent and equally probable.

Participants saw problems sequentially. For each problem, they first observed the lottery format and its payoffs as shown in Figure 1, but probabilities associated with those outcomes were not displayed. For each outcome, participants observed "$p = \ldots$." They were instructed to make the following decision:

> Before choosing between A and B, you have to select the type of information you prefer to see to make your decision. You can see the values of "p," that is, the probabilities associated with each payoff in each lottery; or you can experiment, play the lotteries as many times as you desire before playing for money. What information do you prefer?

Choosing description revealed all the probabilities in the prospect, automatically filling the empty "$p = \ldots$" with "$p = 0.4$," for example. Choosing experience led to a different screen, where participants could sample the lotteries. The sampling screen did not vary across conditions. It displayed two buttons in the middle of the screen labeled with the letter of the lotteries previously observed (A or B). Participants were told, in a written form, that each button was associated with an outcome distribution. Clicking on a button elicited the sampling of an outcome (with replacement) from its distribution. Participants were instructed that they could sample in whatever order they desired and for as long as they wanted. They were encouraged to sample until they felt confident enough to play for a monetary payoff. Once they had sampled sufficiently, they clicked on a button labeled "play for money" that led to a different screen with two buttons labeled "A" and "B."

After participants had stopped sampling (in case of experience) or had observed the probabilities (in case of description) participants read "Choose between one of the following two lotteries." They indicated their desired option by clicking on a button labeled "A" or "B." For each of the seven problems, participants chose process (description or experience) and option (A or B).

After having completed the seven problems, participants in the three conditions completed a Numeracy test (Lipkus, Samsa, & Rimer, 2001) that measured the ability to process basic probability and numerical concepts. This test was chosen over other measures of individual cognitive differences because Peters et al.

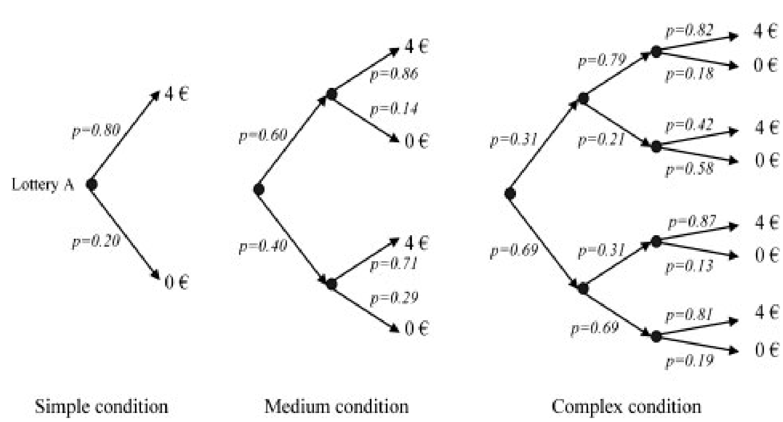

Figure 1. Conditions of increasing complexity. In the three conditions, lottery A pays 4€ with probability 0.80 and 0€ otherwise

(2006) found that participants that scored high in this test were more likely to retrieve and use appropriate numerical principles than participants that scored low. Participants also completed Pacini and Epstein's (1999) rational ability and rational engagement questionnaires taken from the rational experiential inventory. The rational ability scale measured participants' self-reported ability of rational thinking. The rational engagement scale measured the degree to which participants believe that they engage in rational thinking. These scales were included in the experiment because evidence suggests that participants with high scores in rational ability draw larger samples than participants that score low in that scale (Lejarraga, 2006), which can influence the preference for sampling; and because the scales were found to be positively correlated to the number of optimal responses in games of chance comparable to the ones used in this experiment (Pacini and Epstein, 1999).

Problems

Three types of problems were designed (Table 2). Problems 1, 2, and 3 involved the choice between a risky lottery with a rare event and a certain outcome with higher expected value. This type of problem has been the basis of most studies of experience-based choice and in which underweighting of rare events has been mostly manifested.

Problems 4 and 5 involved the choice between two risky lotteries where one includes a rare event. Underweighting of rare events in this type of problem has not been significant in previous studies. For example, in Hertwig et al. (2004), two out of the six decision problems studied involved two risky alternatives. Significant underweighting was observed in only one of them. Hau et al. (2008) included the same two problems in their study but none of them showed significant underweighting. In the free-sampling condition in Rakow et al. (2008), only one of the three problems studied showed significant underweighting. Therefore, problems 1 to 5 were designed to extend the study of the weighting of rare events in decisions from experience, particularly when choosing from experience is not imposed by the experimental design but chosen by the decision maker.

Problems 6 and 7 involved the choice between lotteries that differ slightly in payoffs and probabilities, and involve no rare events. These were designed to explore whether experience favors choice for the highest paying lottery in contexts where the risk of both lotteries is similar and therefore difficult to distinguish by sampling. Typically, this type of problem has been omitted in the literature on experience-based choice.

Predictions for choices from description were based on cumulative prospect theory (CPT) using the parameters estimated by Tversky and Kahneman (1992). Like the original prospect theory (Kahneman & Tversky, 1979), CPT accounts for the commonly observed patterns in decisions from description: Underweighting of large probabilities, overweighting of small probabilities, loss aversion, and diminishing sensitivity to outcomes.

For choices from experience, predictions were derived by applying the fractional adjustment model (FAM) (March, 1996) to the sequences of outcomes observed by participants in their individual samples. This associative learning model was used by Weber et al. (2004) and Hau et al. (2008) to predict choices from experience in similar contexts. The model sets the initial probability $p_{i,0}$ to choose option i at 0.5. Each observed outcome x_i affects this probability recursively according to the learning parameter α in the following form:

$$p_{i,t} = \begin{cases} 1 - \left[(1-\alpha)^{x_i}\left(1 - p_{i,t-1}\right)\right] & \text{if } x_i \geq 0 \\ p_{i,t-1}(1-\alpha)^{x_i} & \text{if } x_i < 0 \end{cases}$$

When sampling is finished, the option with the higher probability $p_{i,t}$ is chosen. The learning parameter used for the model ($\alpha = 0.05$) was estimated by Hau et al. (2008) by fitting the FAM to Hertwig et al.'s (2004) data.

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Compensation

The compensation scheme did not vary across conditions and was described before the choice task. Participants were paid 7€ for showing up plus the payoff from lottery 3 and the payoff of one of the other lotteries drawn at random. The average compensation was 11€.

RESULTS OF EXPERIMENT 2

Lottery complexity has a significant influence on the preference for experience. In the *simple* condition, experience choices amounted to 24% of the total, in the *medium* condition 39%, and in the *complex* condition 51%. Thus, although experience was the minority response overall, it increased across conditions and even slightly surpassed description in the complex condition. A negative binomial model was specified to test that complexity favors experience as a source of choice information. The model has the form $Y = \alpha + \beta X + \mu$ where the dependent variable Y is the count of experience-choices across the seven problems; X is the lottery type and takes values from 1 to 3, indicating complexity increasing linearly; and μ is an error term. The estimated $\beta = 0.36$ (SE = 0.09, $z(118) = 3.96$, $p < .001$) shows a positive correlation between lottery complexity and preference for experience.

It might be expected that participants test both experience and description in early decisions for curiosity or to identify the most appealing source of information. In this case, the effect reported above should be larger for the later problems encountered. Indeed, when the negative binomial model is regressed on the last four problems encountered, the effect of lottery complexity on the preference for experience is even stronger ($\beta = 0.57$, SE = 0.12, $z(118) = 5.02$, $p < .001$). Identical results were obtained when fitting Poisson regressions.

An analysis of response times confirms the assertion that increasing complexity is costly for decision makers. Choosing between A and B from description took an average of 18 seconds in the *simple*, 33 seconds in the *medium*, and 41 seconds in the *complex* conditions. The group difference in response times was statistically significant ($\beta = 11.52$, SD = 1.91, $t(118) = 6.03$, $p < .001$).

Description and experience-based choices

Caution must be taken when interpreting choice results because participants self-selected into either the experience or description conditions. Therefore, the comparison of choice behavior between conditions does not provide insight into the description-experience gap. Instead, it reveals patterns derived from consciously selecting either type of information.

Underweighting of rare events derives from the fact that low-probability events tend to be under-represented in small samples given the skew of the binomial distribution (e.g., for samples of 10 draws, a 0.1 probability event will be under-represented 34.9% of the times). In contrast to previous studies of experience-based choice, this experimental design permits participants willing to exert effort to self-select into the experience condition. Participants sampled a mean of 40 draws per problem (20 per lottery) and a median of 36. While these samples are larger than those observed in previous studies (medians of 15 and 17 in Hertwig et al., 2004 and Weber et al., 2004), they are still small to make appropriate inferences. Yet, they suggest that when sampling is made available as a source of information, participants are willing to incur higher effort in information acquisition than when sampling is imposed as the unique source of information.

If rare events in problems 1 to 3 are underweighted, the attractiveness of option A increases. Results revealed a greater underweighting of rare events in experience than in description (Table 2). This difference was significant in problems 2 and 3. While 76% of choices from description followed the pattern predicted by CPT, applying FAM to the observed samples individually only predicted 56% of choices from experience in problems 1 to 3.

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In problems 4 and 5, underweighting of rare events makes option A more attractive. Yet, choices from experience revealed no such preference. Underweighting of rare events has been mainly observed in decisions from experience when a risky alternative that includes a rare event is compared to a certain outcome. When both options are risky, underweighting is not commonly observed. Choices from experience in problems 4 and 5 reproduce this pattern. Decisions from description were correctly predicted by CPT in 74% of the cases, whereas FAM only predicted 57% of the choices made from experience in problems 4 and 5.

Choices from experience in problem 6 were different from problem 7, even though the problems only differed in sign. In problem 6, choices from experience were predominantly for the most probable outcome: Gaining 4€ with probability 0.5. When the problem was framed in terms of losses, choices from experience were for the least possible loss: Losing 4€ with probability 0.5. Based on the samples observed individually, FAM predicted 60% of choices in problems 6 and 7. In description, the opposite pattern is observed. However, as prospects were highly similar, the choice pattern from description revealed almost equal preferences, and therefore CPT predicted 52% of the choices of problems 6 and 7.

In summary, decisions from experience were different from decisions from description. This difference was significant in four out of seven problems. Whereas decisions from description showed effects hypothesized by prospect theory, such as non-linear probability weighting, loss aversion and diminishing sensitivity, decisions from experience varied in less predictable directions. Overall, CPT correctly predicted 68% of choices from description whereas FAM only predicted 57%. FAM in Hau et al. (2008) predicted 65% of the choices in a comparable design. As Weber et al. (2004) point out, although associative learning models capture the updating nature of choice propensity based on experience, they fail to reflect other relevant cognitive processes such as inferences or counterfactual comparisons.

It is important to note that, while CPT is a 5-parameter model for choices from description, FAM is a one-parameter model for choices based on feedback. The intention of this analysis is not to compare the predictive power of both models but to point out that choices from experience appear to be less predictable than choices from description. Additionally, while CPT is considered a well-tested model for choices from description, FAM is one of many learning models that could have been used to predict choices from experience.

Results extend the evidence that underweighting of rare events occurs even when participants self-selected into the experience condition and therefore could be expected to be better equipped against sampling-related biases. Results also extend the observation that underweighting does not tend to occur when choosing between two risky lotteries as in problems 4 and 5.

If the quality of decisions is measured by the profit obtained from choices, experience was more profitable than description. Adding all payoffs from experience and dividing the total payoff by the number of experience-based choices yields a mean payoff of 0.27€ per choice whereas the mean payoff for description-based choices was only 0.16€.

Decisions from description across increasingly complex contexts

Except for problems 1 and 3, there were large differences in the choice pattern across conditions (Table 3). I speculate that two effects may account for the observed behavior. As lotteries become more complex, probability information becomes harder to interpret and attention may be drawn away from probabilities to outcomes. On the one hand, this switch makes the lotteries with the opportunity of outcomes higher than those in other options more attractive, inducing or strengthening an outcome effect. This pattern was observed in problems 4 to 6 and in the *medium* condition of problems 2 and 7. On the other hand, the vague interpretation of probability information makes the choice context ambiguous. For example, in problem 1, an ambiguous interpretation of probability information would reduce the perceived likelihood of outcome A closer to 0.5. Therefore, increasing complexity and ambiguity makes option B more attractive. The effect of ambiguity then, would explain the same choice pattern as a magnitude effect.

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Table 3. Choices by sample size and increasingly complex condition

Decision problem			% of A-choices				
			Experience		Description		
No.	A	B	Samples > 40	Samples ≤40	Simple	Medium	Complex
1	4€, 0.8	3.5€	29	30	17	26	18
2	−3.5€	−4€, 0.8	45	52	15	32	31
3	3€, 0.9	2.8€	40	45	28	28	24
4	2€, 0.9	3€, 0.6	36	34	92	88	68
5	−3€, 0.6	−2€, 0.9	60	48	89	52	45
6	5€, 0.4	4€, 0.5	0	19	29	90	67
7	−5€, 0.4	−4€, 0.5	37	38	59	17	62

Choices suggest that risk taking is highly sensitive to the degree of complexity involved in the task. Notably, disregarding probabilistic information and focusing on outcomes induces more risk-seeking behavior in complex scenarios.

Decisions from large and small samples

Given that the mean sample size was 40 observations per problem, samples larger than 40 were considered *large* and samples smaller than or equal to 40 were considered *small*. Choices from *large* and *small* samples were similar. In all seven problems, differences were non-significant and either strengthened or weakened a pattern but did not change its direction. The same choice behavior was observed when the split between *large* and *small* samples was set at 30, 20, and 15 observations. These findings add to the evidence from Experiment 1, that experience, even when samples are small, is a favorable source of information, leading to accurate frequency estimates and profitable choices. This result contrasts with the observation made by Fox and Hadar (2006) that, based on the two-stage version of CPT, small samples lead to inaccurate probability estimates that influence choice.

Individual differences

The distribution of numeracy scores was highly skewed, with a median score of 9 out of 11 possible correct answers. Following the criterion used by Peters et al. (2006), who also encountered a skewed response distribution, participants were separated by the median score. Participants with scores from 9 to 11 were considered *high* numerates and participants with scores from 0 to 8 were considered *low* numerates. Participants were also split into *high* rational ability and low rational ability by the sample median (35) and also into *high* rational engagement and *low* rational engagement, also by the sample median (37), as suggested by Pacini and Epstein (1999)[1]. Scales were internally reliable as Cronbach's α for rational ability ($\alpha = 0.76$) and rational engagement ($\alpha = 0.81$) were high. Cronbach's measure can also be applied to tests as a measure of generalizability. In this case, Numeracy's $\alpha = 0.60$.

Results show no effect of individual differences on the preference for experience. Nor was there an interaction between these differences and lottery complexity. However, from the participants that self-

[1]Median separation is associated to loss of power, yet, the skewness of the distribution justifies this choice (Peters et al., 2006 and MacCallum, Zhang, Preacher & Rucker, 2002).

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Table 4. Average sample size per option* by personality classification

	Low	High	Difference
Numeracy	15.15	22.70	7.55 ($t = 2.67$, $p < .001$)
Rational ability	17.45	22.49	5.05 ($t = 1.82$, $p = .002$)
Rational engagement	18.68	21.16	2.49 ($t = 0.92$, $p = .126$)

Note: Two-tailed *t*-test for two homoscedastic population samples.
*"option" refers to each of the two alternatives in each decision problem.

selected into the experience condition, those classified as having high numeracy, high rational ability, and high rational engagement, sampled the lotteries more often than participants that scored low in those classifications (Table 4).

Results add evidence to preliminary findings that participants with high scores in the rational ability scale sampled lotteries significantly more often than participants that scored low on that scale (Lejarraga, 2006). These results are also consistent with Rakow et al. (2008) who found that participants with higher scores on a test of working memory capacity draw larger samples in a no-cost sampling design. Participants classified low in the three personality scales were apparently more impressionistic, relying on first impressions derived from smaller samples. Yet, this tendency had no effect on preferences of experience over description.

DISCUSSION OF EXPERIMENT 2

Results suggest that easy tasks favor the analysis of detailed descriptive probabilities and outcomes. However, when facing complex tasks, a substantial number of people prefer less precise information that is easier to interpret. By trading off the precision of descriptive probabilities, participants relied on the simplicity and the "hunch" provided by experience, regardless of individual characteristics tested in this study. Experience appeared as a short-cut to effortful analysis, and adds to the recent evidence that experience serves as a simplifying mechanism for choice (Hertwig & Pleskac, 2008).

General discussion

Two realistic aspects of decisions from experience were explored in the sampling paradigm. First, when imposing a time delay between information acquisition and judgment, both absolute and rank-order frequency judgments from experience were more accurate than those from description. Even though larger samples led to better estimates, average samples were small and still precise. In Experiment 1 experience provided a better information source for deferred frequency judgments, and in Experiment 2 participants showed a tendency to prefer experience over description more as task complexity increased. This pattern of preferences was independent of individual cognitive differences, though these differences did account for the sizes of samples drawn from the lotteries.

Underweighting of rare events from experience was consistent with previous findings. Moreover, results extend this finding as underweighting of rare events was robust to participants that self-selected into the experience condition and therefore might be expected to be better prepared against experience-based biases.

Controlling for different task complexity, decisions by participants choosing from description were consistent with the predictions of cumulative prospect theory. Yet, increasing description complexity made lotteries with higher outcomes more attractive since deriving meaning from probabilistic information became more effortful. Disregarding probabilistic information induced a change in risk-attitudes, revealing a

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greater tendency for higher but riskier outcomes in complex scenarios. This pattern of description-based choice in complex scenarios poses interesting questions that should be explored in future research.

Results from the two studies suggest that, under certain realistic circumstances, experience can be a better source of information than a detailed description. It leads to better deferred frequency judgments and provides a simplified view of the choice-situation in complex scenarios. As a result, interest in descriptive probabilities should be higher in scenarios where it is easily understandable and readily usable, as modeled in the typical sampling paradigm. Traditionally, the interest of decision-makers on probability information has been overestimated. Research suggests that in some realistic contexts, as with affect-rich outcomes (Rottenstreich & Hsee, 2001) or large losses (Bosch & Silvestre, 2006), people do not pay much attention to probability information, and only a minority actively searches for it (Huber, Wider, & Huber, 1997).

Bounded rationality had already highlighted people's limited cognitive capacity which, throughout evolution, has shaped heuristics as alternatives to effortful cognitive thought (Simon, 1955). Russo (1977) illustrated this cognitive limitation in the field. When prices of different products were easily comparable, because they were expressed in ordered unit prices, buyers at a supermarket saved more money from their purchases than when prices were expressed in different units, and were therefore difficult to compare. Results are in line with these views and extend the findings by Payne et al. (1993) on the effort-accuracy trade-off in decision making. In fact, people not only trade-off effort for accuracy in decision strategies but also in the choice of experience or description as a source of information. However, the choice of a less accurate source of information does not lead to worse inferences or choices: As shown here, experience can lead to more precise frequency estimates and more profitable choices. It would be interesting to see whether the effect of more profitable choices from experience than description generalizes to other types of problems.

An implication from this research is that, if people rely on experience in complex scenarios, experience-based biases are magnified in these scenarios and description-based ones undermined. Weber (2006) provides an interesting example in public perception of climate risk. Experts tend to provide the public with detailed forecasts about issues affecting climate change. Yet, issues are so diverse and their interaction so complex that people seem to rely on observed experience. As a result, we are likely to underestimate the risk of climate catastrophes.

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