

BRIEF REPORT

The Affect Gap in Risky Choice: Affect-Rich Outcomes Attenuate Attention to Probability Information

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It has been suggested that people decide differently when faced with affect-rich prospects (e.g., medical side effects) than with prospects triggering more moderate amounts of affect (e.g., monetary losses). Does this potential impact of affect on risky decision making even result in preference reversals? And if so, how do the cognitive processes underlying the respective decisions differ? Using a within-subjects design, the current research contrasted choices between prospects with relatively affect-rich outcomes and choices between prospects with relatively affect-poor but monetarily equivalent outcomes. Across three studies, findings consistently showed a substantial divergence in participants' affect-rich and affect-poor choices, resulting in systematic within-subject preference reversals. This "affect gap" held for outcomes associated both with negative affect (Studies 1 and 3) and with positive affect (Study 2). Furthermore, computational modeling suggested that in affect-poor choice people commonly rely on a compensatory process that trades off outcome and probability, whereas in affect-rich choice (in particular between outcomes invoking negative affect) people more often rely on a noncompensatory, heuristic process that compares outcomes between options while disregarding probabilities. This interpretation is also supported by process data (Study 3) showing that people pay less attention to probability information and conduct more intradimensional comparisons in affect-rich choices than in affect-poor choices.

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Oftentimes, risky decisions involve outcomes that can conjure considerable emotional reactions. Should we travel by plane and tolerate a minimal risk of a fatal terrorist attack or take the car and run the risk of traffic jams and car accidents (Gigerenzer, 2004)? Should we com-

mit to a single partner or enjoy affairs with different partners at the risk of loneliness in old age (Todd, Penke, Fasolo, & Lenton, 2007)? How do people make such decisions? A key idea, harking back to the notion of mathematical expectation and elaborated by Daniel Bernoulli (1738/1954), is that decisions under risk obey the principle of the maximization of *expectation*. The expectation expresses the average of an option's outcomes, each weighted by its probability. The core of many theories of risky decision making is based on this notion of expectation—most prominently, expected utility theory and (cumulative) prospect theory (CPT; Tversky & Kahneman, 1992). Expectation-based models are quite successful in accounting for choices among relatively affect-poor prospects (usually moderate amounts of money; e.g., Glöckner & Pachur, 2012; but see Birnbaum, 2008). It is less clear, however, to

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what extent an expectation-based calculus generalizes to choices involving affect-rich prospects.

Several authors have hypothesized qualitative differences between decisions involving affect-rich prospects (e.g., a possible electric shock) and those involving affect-poor prospects (e.g., a possible \$20 fine; Buechel, Zhang, Morewedge, & Vosgerau (in press); Figner, Mackinlay, Wilkening, & Weber, 2009; Luce, Bettman, & Payne, 1997; Luce, Payne, & Bettman, 1999; for an overview, see Loewenstein, Weber, Hsee, & Welch, 2001).¹ For instance, Rottenstreich and Hsee (2001) have argued that decisions regarding affect-rich outcomes are relatively insensitive to probability. Indeed, in psychophysical experiments, participants' heart rate in anticipation of an electric shock proved to be impervious to the likelihood of the shock (50% vs. 100%; Elliott, 1975). Our first goal in this article is to examine to what extent differences in the way people respond to relatively affect-rich versus affect-poor risky options result in a systematic difference in the actual choices they make—an *affect gap*. To this end, we use an experimental paradigm that permits us to compare one and the same person's choices in affect-rich and affect-poor problems. Rottenstreich and Hsee (2001) contrasted decisions regarding affect-rich outcomes with decisions regarding monetary outcomes, where the monetary outcomes equaled the median willingness-to-pay (WTP) for the affect-rich outcomes obtained in a pilot study (see also McGraw, Shafir, & Todorov, 2010).² We refine this procedure by matching the affect-rich and the affect-poor outcomes for each participant (by using each individual's WTPs). Using this procedure, we demonstrate for the first time the existence of systematic preference reversals between affect-rich and affect-poor choices within individuals.

Our second goal is to examine the cognitive processes underlying this affect gap. For instance, whereas people might rely on an expectation-based calculus in both affect-rich and affect-poor choices, more affective stimuli could prompt more random error relative to less affective stimuli. Alternatively, the affect gap could be fueled by the use of qualitatively different strategies in affect-rich and affect-poor choice. Specifically, it has been proposed that in affect-rich choice people show "probability neglect" (Sunstein, 2002). Despite some suggestive evidence for this notion (e.g., McGraw, Todorov, & Kunreuther, 2011; for

an overview, see Loewenstein et al., 2001), the consideration of probability information in affect-rich and affect-poor choices has not yet been systematically contrasted using formal modeling. Here, we model both kinds of choices using the most straightforward compensatory, expectation-based calculus (*expected value strategy*; EV) and two simple noncompensatory strategies that disregard probabilities (Studies 1 and 3: *minimax heuristic*; Study 2: *maximax heuristic*; Coombs, Dawes, & Tversky, 1970; Savage, 1951; see below). To evaluate the contribution of random choice to the affect gap, we also considered the number of individuals who could not be modeled with either of these strategies and were therefore classified as guessing. We complement these modeling analyses by comparing, to our knowledge for the first time, the process of information acquisition in affect-rich and affect-poor choice (Study 3).

Three studies are reported. In Studies 1 and 3, we contrast affect-rich and affect-poor choice in a domain with negative affect (medical side effects); in Study 2, we consider a domain with positive affect (hotel amenities). In Study 3, we gauge the cognitive processes underlying choice in affect-rich and affect-poor problems using a process-tracing methodology (Mouselab; Payne, Bettman, & Johnson, 1993). In a final set of analyses, we explore the extent to which differences in both kinds of problems are associated with differences in probability weighting. Specifically, Rottenstreich and Hsee (2001) proposed that CPT's weighting function—capturing how objective probabilities are translated into decision weights—has a more strongly inverse S-shaped curvature in affect-

¹ Consistent with previous research (Slovic & Peters, 2006), we use the term "affect" "to mean the specific quality of "goodness" or "badness" (a) experienced as a feeling state (with or without consciousness) and (b) demarcating a positive or negative quality of a stimulus" (p. 322). In other words, affect is construed to be part of the representation of a stimulus.

² Note that the WTP procedure, although not undebated (e.g., Carson, Flores, & Meade, 2001), is commonly used in behavioral economics to measure how people value non-monetary outcomes (e.g., Carson, 2012). As noted by Loewenstein et al. (2001), cognitive evaluations—such as WTP responses—and affective ratings can to some extent diverge because the latter also take account of more subjective factors such as vividness or the immediacy of the outcomes.

rich than in affect-poor choice. Permitting such difference in probability weighting, CPT (which is based on an expectation core) may offer the best account for both kinds of choices.

Study 1: Is There an Affect Gap—and What Underlies It?

Method

Participants. Forty students (29 women; average age = 23.4 years, $SD = 4.6$) from the University of Basel participated, receiving 7.50 Swiss Francs or course credits as compensation. The sample size had been determined in advance.

Materials, design, and procedure. We used 12 medical side effects as affect-rich stimuli (Table 1; medical outcomes have often been assumed to involve high levels of affect; e.g., Loewenstein, 2005; Redelmeier & Kahneman, 1996). Participants were presented with four tasks on a computer. In the *monetary evaluation task*, they indicated their willingness-to-pay (WTP; in Swiss Francs) to avoid each of the 12 side effects, which were presented in an order determined randomly for each participant. Specifically, they were asked to imagine that they had an (unspecified) illness, and that two equally effective drugs were available to treat it.

Table 1

Monetary Equivalents of the Affect-Rich Outcomes and Affect Ratings of the Affect-Rich Outcomes and Their Monetary Equivalents (as Obtained in the Monetary Evaluation Task) in Studies 1 and 2

Affect-rich outcome	Monetary equivalents (in Swiss Francs)			Affect ratings		
	5%	50%	95%	Affect-rich outcome <i>M (SD)</i>	Monetary equivalent <i>M (SD)</i>	95% CI of difference
Study 1 (negative domain)						
Memory loss	-400	-50	-9	9.50 (1.09)	7.48 (2.41)	[1.28, 2.77]
Depression	-150	-35	-3.5	8.75 (1.84)	6.60 (2.73)	[1.22, 3.08]
Hallucinations	-200	-30	0	8.50 (2.24)	5.78 (2.78)	[2.05, 3.40]
Speech disorder	-125	-30	-4.5	8.28 (1.52)	6.15 (2.64)	[1.38, 2.87]
Dizziness	-75	-20	-4.5	7.15 (1.78)	4.65 (2.40)	[1.84, 3.16]
Insomnia	-100	-20	-3	5.98 (2.26)	4.10 (2.36)	[1.07, 2.68]
Trembling	-65	-15	-2.5	5.28 (1.99)	3.90 (1.91)	[0.66, 2.09]
Itching	-40	-15	-2	5.20 (2.00)	3.63 (2.07)	[1.01, 2.14]
Flatulence	-55	-15	-2	4.73 (1.97)	3.63 (2.27)	[0.36, 1.84]
Diarrhea	-75	-10	-1.5	5.30 (2.05)	3.70 (1.84)	[0.94, 2.26]
Fever	-80	-10	-2	5.03 (2.15)	3.88 (2.17)	[0.41, 1.89]
Fatigue	-50	-10	0	4.08 (2.04)	2.95 (2.05)	[0.55, 1.70]
Study 2 (positive domain)						
Sea location	10	100	400	8.59 (1.72)	7.58 (2.28)	[0.50, 1.53]
Sauna and massage	0	72.5	325	7.78 (2.28)	6.78 (2.75)	[0.47, 1.53]
Beach weather	0	60	350	7.99 (1.93)	6.41 (2.87)	[0.88, 2.27]
Sea water quality	0	50	300	8.00 (1.91)	6.40 (2.74)	[0.99, 2.21]
Sea view	0	50	250	7.88 (1.91)	6.13 (2.85)	[1.19, 2.31]
Air conditioning	0	50	270	7.05 (2.12)	6.13 (2.88)	[0.33, 1.52]
Swimming pool	0	50	200	7.05 (2.15)	5.80 (2.93)	[0.68, 1.82]
Three-star chef	0	50	200	6.69 (2.32)	5.78 (2.95)	[0.29, 1.53]
Driver	0	50	400	6.60 (2.74)	6.15 (3.24)	[-0.20, 1.1]
Cocktails	0	42.5	190	7.05 (2.26)	5.64 (2.90)	[0.79, 2.04]
Balcony	0	30	225	6.83 (2.16)	5.51 (2.72)	[0.72, 1.91]
Sights	0	30	200	6.45 (2.19)	5.26 (3.20)	[0.55, 1.82]
Jacuzzi	0	30	200	6.19 (2.76)	5.31 (2.88)	[0.21, 1.54]
Safe	0	12.5	100	4.43 (2.32)	4.38 (2.78)	[-0.53, 0.63]
Free internet	0	10	125	5.86 (2.53)	4.41 (2.67)	[0.89, 2.01]

Note. CI = confidence interval. Shown are median (i.e., 50% percentile) monetary evaluations of the affect-rich outcomes as well as (to give an impression of the variability of the evaluations) the 5% and 95% percentiles. The affect ratings are shown for the affect-rich outcomes listed in the first column as well as for their monetary equivalents. The 95% CIs refer to the difference between the mean affect ratings for the affect-rich outcomes and the mean affect rating for their monetary equivalents (i.e., willingness-to-pay).

One drug had a specific side effect (occurring with certainty), whereas the other had no side effects. Using the keyboard, participants typed in the extra amount of money they would be willing to pay for a package of the drug without the side effect, relative to a same-size package of the drug with the side effect.

Next, participants were presented with a lottery task consisting of two parts. In the *affect-rich lottery task*, they encountered 13 lottery problems (in random order), in each of which they had to choose between two drugs. Each drug could lead to a particular side effect with some probability. Across the problems, the probability of the side effect varied between 0.5% and 100%. To decrease the chance that one option would dominate the other, and to boost the chance that EV and minimax would make opposite predictions, the problems were constructed as follows: Based on the median monetary evaluation of each side effect obtained in a pilot study, side effects were paired with probabilities such that the expected value of the drug with the more adverse side effect (i.e., with the higher median WTP in the pilot study) was more attractive than that of the drug with the less adverse side effect. (A list of all affect-rich problems used can be found in the supplemental online material.) In the *affect-poor lottery task*, participants were presented with the same lottery problems as in the affect-rich task (in random order), but with the side effects replaced by the monetary amounts (i.e., WTPs) that the individual had specified in the monetary evaluation task. For example, consider a participant who specified a WTP of 20 Swiss Francs to avoid fever and 25 Swiss Francs to avoid insomnia. In the affect-rich problem she would be presented with a choice between drug A, leading to fever with a probability of 15% (no side effects otherwise), and drug B, leading to insomnia with a probability of 10% (no side effects otherwise). In the corresponding affect-poor problem, she would then be presented with a choice between lottery A, leading to a loss of 20 Swiss Francs with a probability of 15% (nothing otherwise), and lottery B, leading to a loss of 25 Swiss Francs with a probability of 10% (nothing otherwise).³ The order in which the affect-rich and the affect-poor parts of the lottery task were presented was counterbalanced across participants.

The final task was an *affective evaluation task*, in which participants indicated the amount of negative affect triggered by each outcome (presented in random order). The task consisted of two parts (their order was counterbalanced across participants). First, each participant was asked to imagine that she had lost a bet and would have to pay an amount of money. For each of her WTPs provided in the monetary evaluation task, she now indicated on a scale from (1 = *not upset at all*) to (10 = *very upset*) the amount of negative affect she would experience if she had to pay this amount.⁴ Second, the participant was asked to imagine that she was required to take a drug and would experience a side effect. For each of the 12 side effects (presented in random order), she indicated how upset she would be by its occurrence.

Results

Monetary and affective evaluation.

Separately for each side effect, Table 1 (upper panel) shows the median response in the monetary evaluation task as well as (to convey the responses' variability) the 5th and 95th percentiles; also shown are the mean ratings in the affective evaluation task for each side effect and its monetary equivalent (i.e., WTP). The affect ratings were analyzed using a 2 (outcome class: side effects vs. monetary loss) \times 12 (outcome

³ In the affect-rich problem, each drug led to a side effect (with some probability) or to no side effect (with the complementary probability). In the affect-poor problem, the equivalent of the occurrence of no side effect was the occurrence of a loss of zero, under the assumption that "no side effect" is the reference point in the affect-rich problem. This assumption is not without problems, however, as the evaluation of the drug may to some extent be affected by the disutility of being sick. Despite this complication, it is important to note that possible mismatches in the reference point between the affect-rich and the affect-poor problems cannot explain our key finding, namely that affect impacts probability sensitivity: differences in the reference point would translate into differences in outcome sensitivity (as captured by the exponent of CPT's value function); they cannot explain differences in the probability weighting function reported in a later section.

⁴ Specifically, we used the German term "sich ärgern," which refers to an emotion ranging between being upset, angry, and annoyed. Suter, Pachur, and Hertwig (2013a) showed that the amount to which an outcome triggered the emotion "sich ärgern" is highly correlated with the triggering of other negative emotions, such as fear, anger, sadness, and disdain, as well as with an overall affective response score.

repeated-measures analysis of variance (ANOVA; both factors were within-subjects). There was a significant main effect of outcome class, $F(1, 39) = 54.08$, $p = .001$, $\eta_p^2 = .581$, indicating that the side effects triggered a higher amount of negative affect than did their monetary equivalents. This was the case for each of the 12 side effects. This finding supports our characterization of side effects and monetary losses as (relatively) affect-rich and affect-poor outcomes, respectively.

Choices. In those problems where the two lotteries had different expected values (the expected values of the affect-rich options were calculated using each individual's WTPs for the respective side effects), the option with the higher expected value was chosen considerably less often in the affect-rich than in the affect-poor problems: $M_s = 49.4\%$ ($SD = 17.0$) versus 61.0% ($SD = 21.0$), $t(39) = -2.54$, $p = .01$. Although affect-rich and affect-poor problems were matched to be monetarily equivalent, people often indicated different preferences across the two contexts: on average, individuals reversed their choices between the affect-rich and the corresponding affect-poor problem 46.4% ($SD = 24.5$) of the time.

Strategy classification. What lies behind this affect gap? We modeled people's choices using the EV strategy and the minimax heuristic (Savage, 1951). According to the EV strategy, the weighted (by probability) outcomes of each option are integrated and the option with the highest expected value is chosen. According to minimax, the options are compared with regard to their worst outcomes and the option with the more attractive worst outcome is chosen; minimax thus disregards probabilities altogether. We used EV and minimax to model choices separately for the affect-poor and the affect-rich problems. To derive the strategies' predictions in the affect-rich problems, we used each individual's WTPs (from the monetary evaluation task) as a proxy for how he or she evaluated the side effects.⁵ When both strategies gave rise to a prediction, they arrived at opposite choices in, on average, 39.3% ($SD = 22.2\%$) of cases. Using a maximum likelihood approach, we classified each participant to the strategy with the best fit (cf. Pachur & Galesic, 2013; Pachur & Marinello, 2013). Specifically, for

each participant i the goodness of fit of strategy k across N lotteries was determined as

$$G_{i,k}^2 = -2 \sum_{j=1}^N \ln[f_j(y)], \quad (1)$$

where $f_j(y)$ represents the probability with which the strategy predicts an individual choice y in lottery problem j . If lottery A was chosen, $f_j(y)$ was the probability that the strategy predicted the choice of lottery A over lottery B, $p_j(A,B)$. If lottery B was chosen, $f_j(y)$ was the probability that the strategy predicted the choice of lottery B, $1 - p_j(A,B)$. $p_j(A,B)$ was defined using an exponential version of Luce's choice rule (also known as softmax; e.g., Sutton & Barto, 1998):

$$p_j(A, B) = \frac{e^{\varphi \cdot V(A)}}{e^{\varphi \cdot V(A)} + e^{\varphi \cdot V(B)}}, \quad (2)$$

where for EV the subjective valuations of lotteries A and B, $V(A)$ and $V(B)$, were defined as $V(A) = x_A \times p_A$ and $V(B) = x_B \times p_B$, respectively (with x and p being the outcome and probability of the nonzero outcomes of the lottery, respectively); for minimax, they were defined as $V(A) = x_A$ and $V(B) = x_B$. The adjustable parameter $\varphi > 0$ is a choice sensitivity parameter (estimated for each participant) specifying how sensitive the predicted $p_j(A,B)$ is to differences in the subjective valuation of the lotteries. Participants were classified as following the strategy with the best fit (i.e., lowest G^2). If the best-fitting strategy's G^2 equaled (or was higher than) the value of G^2 under random choice (i.e., with $p[A,B] = 0.5$), the individual was classified as "guessing or using another strategy." (The best-fitting parameter values and the strategies' model fits in Studies 1 to 3 are reported in the supplemental online material.)

What can this analysis tell us regarding differences in the processes underlying the affect gap? Because repeated choices are rarely perfectly consistent (e.g., Hey, 2001; Rieskamp, 2008), the gap could simply be due to unsystematic responding in the lottery problems. This

⁵ Additional analyses, reported in the supplemental online material, showed that for all three studies the results of the strategy classification were highly similar when participants' affective—rather than monetary—evaluations of the outcomes were used to implement the strategies.

would be consistent with a strategy classification showing no differences in strategy use between affect-rich and affect-poor problems. An alternative reason for the gap could be that the WTPs obtained in the monetary evaluation task provide only a rather noisy measure of people's actual evaluations of the side effects (see Kahneman, Ritov, & Schkade, 1999), thus violating the assumed monetary equivalence between affect-rich and affect-poor problems. Similarly, people might choose less consistently in the face of affective stimuli. In either case, there should be more participants that could not be modeled (and were thus classified as guessing) in the affect-rich than in the affect-poor prob-

lems. Finally, the affect gap could arise because people use qualitatively different choice strategies in the two sets of problems. Specifically, maximization of expectation as represented by the EV strategy may be restricted to affect-poor choice, whereas affect-rich choices may disregard probabilities, as represented by minimax.

The top panel of Figure 1 shows the distribution of participants classified as following EV, minimax, and guessing (or another strategy), respectively. The results suggest clear differences in strategy use between the affect-rich and the affect-poor problems. Specifically, more participants were classified as following EV in the affect-poor than in the affect-rich

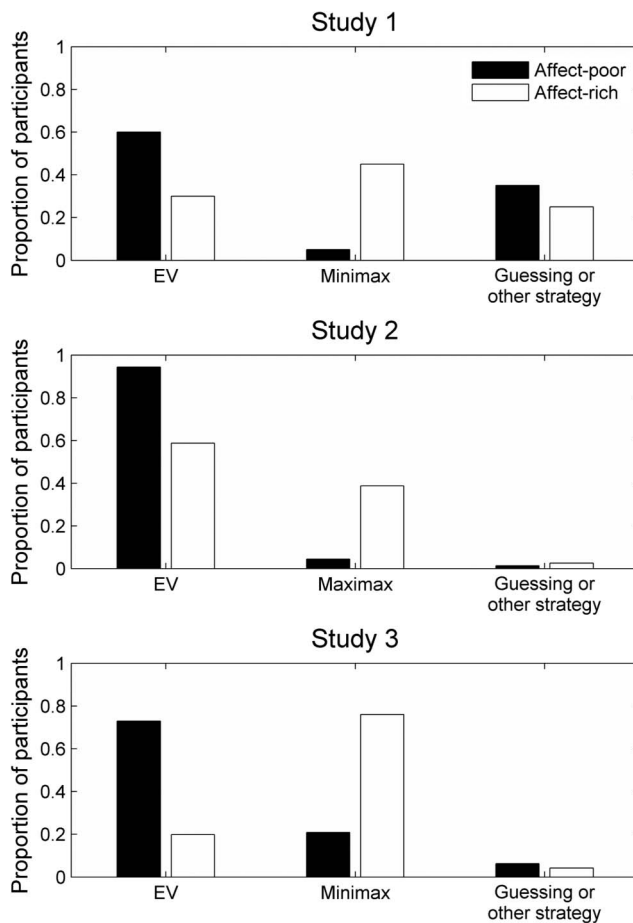


Figure 1. Proportion of participants classified as following the compensatory expected value strategy (EV), the noncompensatory heuristics minimax (Studies 1 and 3) and maximax (Study 2), or as guessing/using another strategy, separately for the affect-poor and the affect-rich lottery problems.

problems (60.0% vs. 30.0%, $z = 2.697$, $p = .007$). For minimax, the opposite trend emerged (5.0% vs. 45.0%, $z = -4.131$, $p = .001$). Equally important, the percentage of participants classified as guessing (or using another strategy) was similar across affect-poor and affect-rich problems (35.0% vs. 25.0%, $z = 0.976$, $p = .329$). Thus, the observed affect gap is unlikely to be due to a lack of reliability in participants' WTP responses (investigating this issue directly—by asking each participant to provide WTPs twice—Pachur & Galesic, 2013, also found no evidence that the affect gap was driven by unreliable WTP responses). These results suggest that the affect gap may, at least in part, be caused by people's use of different strategies. To put this interpretation to a further test, we specifically analyzed those instances for which a participant reversed his or her preference between the affect-rich and the affect-poor problems *and* where minimax and EV predicted opposite choices. Here participants' choices were consistent with EV in the affect-poor problems and at the same time consistent with minimax in the affect-rich problems in 86.4% ($SD = 28.8$) of cases.

Study 2: Does the Affect Gap Generalize to a Domain Involving Positive Affect?

Study 2 turns to outcomes with positive valence. Individuals chose between options in which they could obtain a positive outcome with some probability (and nothing otherwise). We modeled their choices using maximax (Coombs et al., 1970), minimax's twin in the gain domain. Like minimax, maximax disregards probability information and thus embodies probability neglect. Specifically, it examines the options' maximum (i.e., best) outcomes and chooses the one with the most attractive maximum outcome.

Method

Participants. Eighty students (55 women; average age = 25.5 years, $SD = 6.4$) from the University of Basel participated, receiving 7.50 Swiss Francs or course credits as compensation. The sample size had been determined in advance.

Materials, design, and procedure. Fifteen hotel amenities (Table 1) served as affect-rich

stimuli, with which we constructed 13 lottery problems using the same method and similar probability levels as in Study 1 (for a complete list, see the supplemental online material). Participants were again presented with a monetary evaluation task, affect-rich and affect-poor lottery tasks, and an affective evaluation task (gauging their happiness about the occurrence of specific outcomes). Concerning the affect-rich problems, participants were asked to imagine that their employer had given them a basic 1-week holiday package as an end-of-year bonus. They could supplement this package with amenities by participating in a raffle. In the affective evaluation task, each participant was asked to imagine that she had won a bet and would receive a certain amount of money. For each of the WTP amounts recorded in the monetary evaluation task, she now indicated on a scale from 1 = *not happy at all* to 10 = *very happy* the amount of positive affect she would experience if she won this amount. In addition, the participant was asked to imagine that she had bought a basic holiday package, but would get a particular amenity for free; for each amenity, she indicated how happy she would be to receive it.

Results

Monetary and affective evaluations.

Table 1 (lower panel) shows, for each amenity, the median response in the monetary evaluation task (and the 5th and 95th percentiles) as well as the mean ratings in the affective evaluation task for the amenities and their monetary equivalents. The affect ratings were analyzed using a 2 (outcome class: amenities vs. monetary gain) \times 12 (outcome) repeated-measures ANOVA (both factors were within-subjects). The results showed a significant main effect of outcome class, $F(1, 79) = 29.6$, $p = .001$, $\eta_p^2 = .273$, indicating that the amenities triggered a higher amount of positive affect than did their monetary equivalents. This held for 13 of the 15 amenities. As expected, the hotel amenities were thus relatively affect-rich (in comparison to their monetary equivalents).

Choices. As in Study 1, the option with the higher expected value was selected less frequently in the affect-rich than in the affect-poor problems: $M_s = 70.5\%$ ($SD = 14.7$) versus 83.9% ($SD = 13.8$), $t(79) = -5.60$, $p = .001$.

There were, on average, 36.7% ($SD = 15.4$) within-subject preference reversals; the affect gap thus also seems to hold in a domain involving positive affect.

Strategy classification. Using the same procedure as in Study 1, we classified participants as following EV, maximax, or guessing (or another strategy). When both EV and maximax made a prediction, they suggested opposite choices in, on average, 24.9% ($SD = 19.2\%$) of cases. The middle panel of Figure 1 again indicates substantial differences in strategy use: more people were classified as following EV in the affect-poor than in the affect-rich problems, 94.4% versus 58.8%, $z = 5.318$, $p = .001$. For maximax, the opposite pattern was obtained, 4.4% versus 38.8%, $z = -5.287$, $p = .001$. Hardly any participant was classified as guessing (or using another strategy) in the affect-poor and the affect-rich problems (1.3% vs. 2.5%, $z = -0.583$, $p = .56$). Focusing on cases where individuals reversed their choices between the affect-rich and the corresponding affect-poor problems *and* where maximax and EV predicted opposite choices, participants' choices were consistent with EV in the affect-poor and with maximax in the affect-rich problems in 90.0% ($SD = 25.2$) of cases. These findings in choices involving positive affect (gain domain) echo those obtained in a domain involving negative affect (loss domain; Study 1) and suggest that the preference reversals are systematic and not merely due to random factors.

Study 3: Tracing Process in Affect-Rich and Affect-Poor Problems

We next used a process tracing method to test the thesis suggested by the formal modeling that people are more likely to rely on a process that pays less heed to probabilities in affect-rich than in affect-poor choice. Specifically, we used the Mouselab methodology (Payne et al., 1993) to record how individuals acquired information before making a choice. In Mouselab, the relevant information (i.e., outcomes and probabilities) are “hidden” behind boxes, but can be called upon by clicking on the respective box (Figure 2). We tested two predictions about this process of information acquisition. The first concerns the acquisition frequencies of outcome and probability information in affect-rich and affect-poor problems. According to our strategy

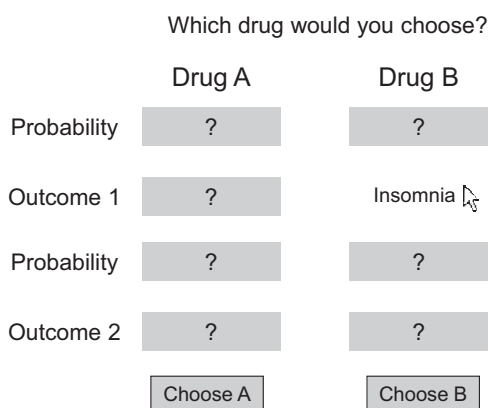


Figure 2. Presentation of the lotteries using Mouselab in Study 3 (illustrated here with affect-rich material and a vertical presentation format).

classification results (Figure 1)—which found more evidence for the use of heuristics that disregard probabilities in affect-rich than in affect-poor problems—information acquisition should involve fewer examinations of probabilities in choices among affect-rich outcomes. The second prediction concerns the direction of search, that is, the sequence of transitions between subsequent acquisitions. Transitions are *dimension-wise* if they occur between boxes belonging to the same dimension (e.g., Outcome 1); transitions are *alternative-wise* if they occur between boxes within an option. Compensatory strategies are usually associated with more frequent alternative-wise transitions than noncompensatory strategies (e.g., Johnson, Schulte-Mecklenbeck, & Willemsen, 2008; Pachur, Hertwig, Gigerenzer, & Brandstätter, 2013; Payne & Braunstein, 1978). Therefore, if people are more likely to follow a compensatory, expectation-based calculus in affect-poor than in affect-rich problems, search direction should be more alternative-wise in the former than in the latter. If, however, a compensatory process underlies choices both in affect-rich and affect-poor problems, then direction of search should be similar across both.

Method

Participants. Ninety-six students (63 women; average age = 24.9 years, $SD = 4.96$) from the University of Basel participated, receiving 7.50 Swiss Francs or course credits as

compensation. The sample size had been determined in advance.

Materials, design, and procedure. We used the same material, tasks, design, and procedure as in Study 1, with the exception that the lottery tasks were presented using a Mouselab program (once a box was clicked, it remained open as long as the mouse was pressed). The location of the boxes on the screen (horizontal vs. vertical presentation format) and the order of information (probability information first vs. outcomes first) was counterbalanced across participants.

Results

Affect ratings, choices, and strategy classification. Monetary evaluations and affective responses closely replicated those obtained in Study 1 (supplemental online material). Similarly, the pattern of choices replicated those found in Study 1: Among lottery problems with different expected values, participants chose the option with the higher expected value considerably less often in the affect-rich than in the affect-poor problems, $M_s = 56.71\%$ ($SD = 21.0$) versus 71.66% ($SD = 18.60$), $t(79) = -5.43$, $p = .001$. Overall, there were, on average, 42.6% ($SD = 17.5$) preference reversals between the affect-rich and the corresponding affect-poor problems. As in Study 1, we classified participants as following EV, minimax, or guessing (or another strategy). Figure 1 (bottom panel) shows that the percentage of participants classified as following EV was again substantially higher in affect-poor than in affect-rich problems (72.9% vs. 19.8% , $z = 7.38$, $p = .001$), whereas for minimax the pattern was reversed (20.8% vs. 76.0% , $z = -7.654$, $p = .001$). The percentage of participants in the category “guessing or other strategy” was low and similar across both tasks (6.3% vs. 4.2% , $z = 0.652$, $p = .515$). When the analysis was focused on cases where preferences were reversed between affect-rich and affect-poor problems and where minimax and EV made opposite predictions (which occurred, on average, in 38.8% , $SD = 23.1\%$, of cases), another result replicated: In 86.4% ($SD = 28.6$) of cases, choices followed EV in the affect-poor problems but minimax in the affect-rich problems.

Process tracing. Are people less likely to acquire probability information in affect-rich problems than in affect-poor ones, as suggested

by our modeling analyses? In the affect-poor problems, participants distributed their acquisition effort equally across outcome and probability information. On average, in each lottery they clicked on outcome information 5.58 ($SD = 1.95$) times and on probability information 5.53 ($SD = 2.30$) times, $t(95) = 0.36$, $p = .72$. In the affect-rich problems, by contrast, participants acquired outcomes more frequently than probabilities: $M_s = 4.46$ ($SD = 1.51$) versus 4.00 ($SD = 1.64$), $t(95) = 4.04$, $p = .001$. Furthermore, participants made fewer acquisitions in the affect-rich than in the affect-poor problems: $M_s = 8.47$ ($SD = 2.96$) versus 11.12 ($SD = 4.05$), $t(95) = -7.42$, $p = .001$. This result is consistent with the thesis of more heuristic processing in affect-rich problems (under the assumption that heuristic processing is tantamount to ignoring part of the information).

Does direction of search confirm this picture? To this end, we computed the SM index (Böckenholt & Hynan, 1994; supplemental online material). The higher the SM index, the more search proceeds in an alternative-wise fashion. SM was indeed lower in the affect-rich than in the affect-poor problems, $M_s = 1.95$ ($SD = 7.65$) versus 3.20 ($SD = 5.97$), $t(95) = -2.02$, $p = .05$. Thus, the process-tracing data converges with the conclusions from the computational modeling. Affect-poor prospects appear to trigger a compensatory process that integrates outcome and probability information; affect-rich prospects, in contrast, appear to be more likely to trigger a noncompensatory process in which probabilities play only a secondary role relative to outcomes and in which options are compared along individual dimensions.⁶

⁶ Additional analyses using mixed-effects linear modeling (with “participants” as a random factor and “strategy” as a fixed factor) also showed a convergence between strategy classification and process measures. Specifically, participants classified as following minimax made, on average, fewer acquisitions of probability information than did participants classified as following EV, $M_s = 4.36$ ($SE = .22$) versus 5.20 ($SE = .23$), $F(1, 180) = 7.00$, $p = .009$; moreover, minimax users showed a lower SM value than did EV users, $M_s = 1.47$ ($SE = .70$) versus 3.75 ($SE = .711$), $F(1, 180) = 5.29$, $p = .023$.

Is the Affect Gap Consistent With Differences in Probability Weighting?

Rottenstreich and Hsee (2001) proposed that, relative to affect-poor choice, affect-rich choice gives rise to a more strongly inverse S-shaped curvature of CPT's probability-weighting function. Is there evidence for such differences in probability weighting in our data? And how well does CPT describe affect-rich choices relative to a simple heuristic that embodies probability neglect? To investigate these questions, we fitted CPT, minimax (Study 1 and 3) and maximax (Study 2) to the aggregate choice data of each study, separately for the affect-poor and the affect-rich problems.⁷ In two-outcome lotteries with only one nonzero outcome (that we used in our studies) CPT determines the V of lottery A as

$$V(A) = \sum_{i=1}^n v(x_i)w(p_i), \quad (3)$$

where $v(x_i)$ is the subjective value of outcome x_i , defined according to the following value function:

$$v(x) = \begin{cases} x^\alpha, & \text{if } x \geq 0 \\ -(-x)^\alpha, & \text{if } x < 0 \end{cases} \quad (4)$$

The parameter α reflects the sensitivity to differences in outcomes and is assumed to lie in the range $[0, 1]$. This yields a concave value function for gains and a convex one for losses.⁸ In Equation 3, $w(p_i)$ is the probability-weighting function that translates objective probabilities into subjective decision weights (cf. Goldstein & Einhorn, 1987):

$$w(p) = \frac{\delta p^\gamma}{\delta p^\gamma + (1-p)^\gamma}. \quad (5)$$

The parameter γ reflects the sensitivity to differences in probabilities and is assumed to be in the range $[0, 1]$, with lower values yielding a more inverse S-shaped curvature. The parameter δ governs the elevation of the weighting function and can be interpreted as a measure of risk aversion (with $\delta > 0$; cf. Gonzalez & Wu, 1999). CPT predicts that the lottery with the more attractive V is preferred.

For minimax and maximax, the predicted choice probability $p(A, B)$ was determined using a choice rule that combines the softmax rule (Equation 2) and a contribution from random guessing (see Loomes, Moffatt, & Sugden, 2002)⁹:

$$p(A, B) = (1 - g) \cdot \frac{e^{\varphi \cdot V(A)}}{e^{\varphi \cdot V(A)} + e^{\varphi \cdot V(B)}} + g/2. \quad (6)$$

The parameter φ again represents the choice sensitivity (Equation 2); g is the probability of random guessing. For comparability, we used the same choice rule for CPT, but with $V(A)$ and $V(B)$ representing the valuation of the lotteries A and B according to Equation 3.¹⁰

We fitted the model parameters to maximize the likelihood of the observed choices (i.e., using G^2 as index of fit). To reflect the main assumptions of CPT, the parameter values were restricted as follows (see Rieskamp, 2008): $0 < \alpha \leq 1$; $0 < \gamma \leq 1$; $0 < \delta \leq 10$. For CPT and minimax (maximax), the choice sensitivity parameter was restricted to be $0 < \varphi \leq 20$; the guessing parameter was restricted to be $0 \leq g \leq 1$. The parameter estimation was based on a combination of a grid search and subsequent optimization using the simplex method (Nelder & Mead, 1965), with the 20 best-fitting value

⁷ As five parameters cannot be reliably estimated based on 13 binary choices, fitting CPT to individual participants was not possible.

⁸ Because the lottery problems we investigated did not contain mixed lotteries (i.e., involving gains and losses within the same lottery), we did not fit a loss-aversion parameter.

⁹ Previous investigations considered mainly choice rules with either a constant error probability *or* an error that is dependent on the ratio of the attractiveness of the options (e.g., Blavatsky & Pogrebna, 2010; Rieskamp, 2008; Stott, 2006). The choice rule used here combines both. Additional analyses testing other choice rules (including the ratio-dependent probit and Luce choice rules) showed that softmax combined with a constant error probability (Equation 6) yielded the best model fit (in terms of BIC). We did not apply this two-parameter choice rule for the strategy classification in Studies 1 to 3 as, because of the low number of choices for each participant, two parameters could not be reliably estimated on the individual level.

¹⁰ When the parameters were estimated using softmax alone (Equation 2), across all three studies the same qualitative pattern of CPT's parameter values emerged.

Table 2
Parameter Values of Cumulative Prospect Theory (CPT) Fitted to the Aggregate Choices in Studies 1 to 3

CPT Parameter	Study 1		Study 2		Study 3	
	Affect-poor	Affect-rich	Affect-poor	Affect-rich	Affect-poor	Affect-rich
α	0.055	1	0.190	0.396	0.474	0.388
γ	0.344	0.001	0.599	0.624	0.597	0.001
δ	1.788	0.095	2.197	7.332	0.931	5.277
φ	20	0.384	7.709	0.959	1.729	1.503
g	0.454	0.529	0.033	0.268	0.045	0.230
G^2	624.74	688.41	687.90	1212.49	1382.08	1375.68

Note. G^2 indicates the CPT's goodness of fit. The G^2 expected under chance is 720.9, 1,441.7, and 1,730.1 in Studies 1, 2, and 3, respectively.

combinations from the grid search serving as starting points for simplex.

The best-fitting CPT parameters are shown in Table 2. (The parameter values for the choice rule of minimax and maximax are reported in the supplemental online material.) In Studies 1 and 3 (negative affect) and in support of Rottenstreich and Hsee's (2001) thesis, the curvature of the weighting function was more strongly S-shaped (as indicated by a lower γ parameter) for the affect-rich than for the affect-poor problems. In Study 2 (positive affect) the γ values did not differ between both sets of problems. In addition, there was some indication for more pronounced risk aversion in affect-rich problems in losses (Studies 1 and 3) and for more pronounced risk seeking in affect-rich problems in gains (Study 2)—as indicated by a more linear value function (i.e., higher α), a more elevated weighting function (i.e., higher δ ; see Gonzalez & Wu, 1999), or both. Finally, choice sensitivity (φ) was consistently lower and the contribution of random guessing (g) higher in the affect-rich problems.

How well did minimax (Studies 1 and 3) and maximax (Study 2) account for participants' choices, relative to CPT? To control for differences in model flexibility, we evaluated the models using the Bayesian Information Criterion (BIC; Schwarz, 1978), which penalizes a model for each additional free parameter.¹¹ As can be seen from Table 3, in the affect-poor problems CPT showed a clearly superior fit (i.e., lower BIC) over minimax (Studies 1 and 3) and maximax (Study 2). In the affect-rich problems, by contrast, the fit of the models were similar, with no clear winner.

Taken together, these modeling results show, first, that the affect gap is partially consistent

with the assumption of a more strongly inverse S-shaped weighting function in affect-rich than in affect-poor problems. Yet the notion of probability neglect, as implemented by minimax and maximax, offers a viable alternative account of affect-rich risky choice, even when compared with a compensatory process that permits differences in probability weighting. There are two important caveats in interpreting the modeling results, however. First, although the model comparison with CPT does not favor a noncompensatory over a compensatory process in affect-rich choice (but see Figure 1), it is worth to keep in mind that CPT may to some extent be able to mimic the choices of the noncompensatory strategies minimax and maximax (cf. Johnson & Meyer, 1984; Suter, Pachur, & Hertwig, 2013b). Second, the models were fitted to aggregate choices, and heterogeneity between participants may have distorted the parameter estimates (e.g., Estes & Maddox, 2005). Future studies should therefore attempt to compare the models on the individual level, using a larger number of lottery problems for each participant.

General Discussion

Across three studies, we consistently found that individuals often express systematically different preferences in affect-rich and affect-

¹¹ In order to calculate the BIC for the comparison between CPT and minimax/maximax, we first determined the G^2 for all models based on Equation 1. The BIC of model k was then calculated as $BIC_k = G^2 + m_k \times \ln(n)$, with m_k being the number of free parameters of model k ($m_{CPT} = 5$ and $m_{minimax} = m_{maximax} = 2$) and n being the number of choices.

Table 3

Bayesian Information Criterion (BIC) for Cumulative Prospect Theory (CPT) and Minimax (Studies 1 and 3) and Maximax (Study 2) When Fitted to the Aggregate Choices, Separately for the Affect-Poor and the Affect-Rich Lottery Problems

Model	Study 1		Study 2		Study 3	
	Affect-poor	Affect-rich	Affect-poor	Affect-rich	Affect-poor	Affect-rich
CPT	649.76	713.43	722.63	1,247.22	1,417.72	1,411.32
Minimax	733.33	714.37	—	—	1,700.97	1,410.02
Maximax	—	—	1,416.75	1,309.99	—	—

poor choice tasks—a phenomenon we refer to as the affect gap. We found that affect-rich choices were better modeled by heuristics that disregard probabilities and compare options in terms of their outcomes than by the EV strategy. Assuming that people follow EV in affect-poor problems but minimax and maximax in affect-rich problems accounts for 86%–90% of cases in which people reversed their preferences. Process data further supported the thesis that affect-rich versus affect-poor problems trigger different strategies. In the former, people looked up probabilities less frequently than outcomes and they conducted more intradimensional comparisons than in the latter. To our knowledge, Studies 1–3 offer the first direct experimental and process evidence for the notion (e.g., Gigerenzer, 2004; Reynolds & Nelson, 2007; Slovic, 1987; Sunstein, 2002) that the psychological impact of probability information is diminished when options trigger (stronger) affect. Evidence suggestive of probability neglect in affect-rich situations has been reported previously (e.g., Elliott, 1975; McGraw et al., 2011), but without within-person comparisons of affect-rich and affect-poor choice and without formal modeling and process tracing.

In further analyses, we employed CPT to explore whether differences in affect-rich and affect-poor choice may be a matter of degree (probability weighting) rather than a matter of kind (different strategies). Rottenstreich and Hsee (2001) proposed that “weighting functions will be more S-shaped for lotteries involving affect-rich than affect-poor outcomes.” (p. 185) We indeed found some evidence supporting this thesis; however, based on our model comparison (Table 3), it is equally likely that affect-rich stimuli trigger a process that disregards or at least downgrades probability information.

The thesis that in affect-rich choice probabilities tend to be neglected also fits with findings by DeKay, Hershey, Spranca, Ubel, and Asch (2006). These authors observed that when evaluating medical treatment options, people seem to be unwilling to aggregate over medical outcomes in a compensatory, weighted (by probability) fashion.

How Does the Affect Gap Relate to Other Preference Reversals?

Affect-rich problems and monetarily equivalent affect-poor problems can result in reversed preferences within the same person. Previous research has found preferences to reverse (a) when outcomes are framed as gains versus losses (Tversky & Kahneman, 1981); (b) when objects with an attribute that is difficult to evaluate (i.e., whether a given attribute value is good or bad) are presented separately versus jointly (e.g., Hsee, Loewenstein, Blount, & Bazerman, 1999); and (c) when preferences are elicited with different methods (e.g., choice vs. matching; Lichtenstein & Slovic, 1971; for an overview, see Slovic, 1995). The preference reversals manifested in the affect gap are distinct from these instances. They occur with outcomes that are framed with regard to the same reference point, with the same number of objects in a choice set, and based on the same elicitation method (i.e., a binary choice task). Therefore, it is also unclear how the “prominence hypothesis”—which is often invoked to account for preference reversals between choice and matching (e.g., Tversky, Sattath, & Slovic, 1988) and according to which the different dimensions of an option are weighted differently in different elicitation methods—could explain the affect gap.

Relatedly, the affect gap also seems to be different from the preference reversals triggered by pricing versus choice as discussed by Kahneman et al. (1999). These authors observed that people assessing items from different categories (e.g., myeloma vs. coral reefs) expressed divergent preferences depending on whether they are asked to choose between the items or to state a WTP for each. In our studies, the items always belonged to the same categories (side effects and hotel amenities, respectively), and Kahneman et al. did not observe preference reversals in within-category assessments.

The Functions of Affect

Affect and emotional processing can impact decision making in many different ways (Hertwig & Volz, in press; Slovic & Peters, 2006). What role does affect play in giving rise to the affect gap? The evidence for the use of different strategies in affect-rich and affect-poor problems is consistent with the notion that affect acts “as a spotlight” (Peters, 2006), focusing people’s attention on specific types of information (e.g., outcomes). In addition, the analyses presented in the supplemental online material (Footnote 5) indicate that affect may to some extent also function “as information,” with people treating the amount of affect associated with an outcome as a proximal cue for its subjective value (Schwarz & Clore, 1983; Slovic, Finucane, Peters, & MacGregor, 2002).

Incommensurability: A Limitation?

There is at least one substantial objection to our conclusions concerning the affect gap. McGraw and colleagues (2010) pointed out that affect-rich outcomes are often presented in a nonnumerical format, rendering integration with numerical probability information difficult. Do the differences we observed between affect-rich and affect-poor choice thus merely reflect differences in presentation format? We do not think so. In additional analyses of the choices obtained in Study 3 (supplemental online material), we found reduced sensitivity to the probability of affect-rich outcomes also *within the same* presentation format. For instance, the curvature parameter γ of CPT’s weighting function was also lower in choices involving affect-rich side effects than in choices involving affect-poor side effects. Moreover, using similar ma-

terial as in our Studies 1 and 3, Suter et al. (2013a) found reduced probability sensitivity in affect-rich choices even when the affect-rich outcomes were presented simultaneously with their monetary equivalents.¹² Based on these results, it seems unlikely that probability information is neglected in affect-rich choices primarily because the decision maker would have to go through a process of mental transformation in order to integrate outcome information with (numerical) probabilities.

Implications for Risk Communication

People facing rare-event risks with dreaded outcomes, such as becoming a victim in a terrorist attack, are at risk of making poor decisions (e.g., Gigerenzer, 2004; McGraw et al., 2011; Waters, Weinstein, Colditz, & Emmons, 2009). How can the public’s response to such risks be improved? Rottenstreich and Hsee (2001) argued that “affect-rich outcomes yield pronounced overweighting of small probabilities” (p. 187), implying that a possible corrective intervention is to reduce attention to small probabilities. Interestingly, if the affect gap is caused by the use of heuristics that neglect probabilities, the opposite follows: interventions should aim to *enhance* people’s attention to probability information—for instance, by presenting probabilities as icon arrays (Waters, Weinstein, Colditz, & Emmons, 2007).

Conclusion

We demonstrated a robust affect gap in risky choice. Faced with monetarily equivalent affect-rich versus affect-poor risky outcomes, people tend choose differently, and systematic preference reversals within the same individual can result. Experimental, modeling and process analyses of the mechanisms underlying this affect gap suggest that risky choices do not rest on the notion of mathematical expectation to the same degree in affect-rich as in affect-poor choice. Therefore, aiding people in making better choices under risk may require different

¹² Although our studies and the studies in Suter et al. (2013a) employed a similar approach to study affect-rich choice, the latter investigated only the negative domain and did not use process tracing.

interventions depending on the options' potential to invoke affects.

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