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# How Affect Shapes Risky Choice: Distorted Probability Weighting Versus Probability Neglect

RENATA S. SUTER[1], THORSTEN PACHUR[1]* and RALPH HERTWIG[1]
[1]*Max Planck Institute for Human Development, Berlin, Germany*

ABSTRACT

People's choices between prospects with relatively affect-rich outcomes (e.g., medical side effects) can diverge markedly from their choices between prospects with relatively affect-poor outcomes (e.g., monetary losses). We investigate the cognitive mechanisms underlying this "affect gap" in risky choice. One possibility is that affect-rich prospects give rise to more distortion in probability weighting. Another is that they lead to the neglect of probabilities. To pit these two possibilities against each other, we fitted cumulative prospect theory (CPT) to the choices of individual participants, separately for choices between options with affect-rich outcomes (adverse medical side effects) and options with affect-poor outcomes (monetary losses); additionally, we tested a simple model of probability neglect, the minimax rule. The results indicated a qualitative difference in cognitive mechanisms between the affect-rich and affect-poor problems. Specifically, in affect-poor problems, the large majority of participants were best described by CPT; in affect-rich problems, the proportion of participants best described by the minimax rule was substantially higher. The affect gap persisted even when affect-rich outcomes were supplemented by numerical information, thus providing no support for the thesis that choices in affect-rich and affect-poor problems diverge because the information provided in the former is nonnumerical. Our findings suggest that the traditional expectation-based framework for modeling risky decision making may not readily generalize to affect-rich choices. Copyright © 2015 John Wiley & Sons, Ltd.

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KEY WORDS risky choice; affect; probability weighting; prospect theory; minimax rule

Choices between risky and uncertain options often evoke strong affects. Should David undergo a medical treatment that promises some chance of curing his life-threatening illness but carries the risk of excruciating side effects? Should Tony confess his feelings to Eve and face the risk of rejection? How do people make these choices? The common denominator of many theories of human choice is the assumption that conflicts are mastered by making trade-offs. Since the Enlightenment, it has been believed that the processes by which trade-offs between risks (probabilities) and outcomes (gains or losses) can be made in a rational way are weighting and summing. Numerous theories of human choice—including expected-value theory, expected utility theory (e.g., Bernoulli, 1954), and prospect theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992)—rest on this notion (for an overview, see Johnson & Busemeyer, 2010; but see also Brandstätter, Gigerenzer, & Hertwig, 2006; Li, 1996). These theories typically do not stipulate that the descriptive (let alone normative) appropriateness of an expectation-based calculus may depend on the affective quality of the prospects at hand.

Yet numerous investigations have identified striking differences between choices involving affect-rich (e.g., medical treatments) and affect-poor prospects (e.g., a loss of $40; Buechel et al., 2014; Pachur & Galesic, 2013; Petrova, van der Pligt & Garcia-Retamero, 2014; Petrova, van der Pligt & Garcia-Retamero, 2014; Rottenstreich & Hsee, 2001; for overviews, see Loewenstein, Weber, Hsee, & Welch, 2001; Peters, 2006) and when people were put in an affect-rich state (Nygren, Isen, Taylor, & Dulin, 1996).[1] Pachur, Hertwig, and Wolkewitz (2014) found evidence suggesting that choices between affect-rich prospects are based on qualitatively different cognitive mechanisms than are choices between affect-poor prospects. For instance, in choices between monetary lotteries (affect-poor), 73% of participants were classified as following a strategy that relies on the expected value of the options. In choices between two medications with the risk of adverse side effects such as insomnia (affect-rich; with a monetary structure identical to the affect-poor monetary lotteries), 76% of participants were classified as following a simple strategy that processes only outcome information, the minimax rule (Coombs, Dawes, & Tversky, 1970; Savage, 1951).

However, the Pachur et al. (2014) strategy analysis of the "affect gap" in risky choice does not conclusively rule out the possibility that participants employed some kind of expectation-based calculus, even when choosing between affect-rich prospects. Indeed, Rottenstreich and Hsee (2001) proposed that choices involving affect-rich and affect-poor prospects could both be accommodated by cumulative prospect theory (CPT; Tversky & Kahneman, 1992)—a model that assumes that people choose as if they were multiplying some function of probability and value, and then maximizing. It was argued that the key to the systematic differences in affect-rich and affect-poor choices lies in different degrees of nonlinear probability weighting. Testing this account,

*Correspondence to: Thorsten Pachur, Center for Adaptive Rationality, Max Planck Institute for Human Development, Lentzeallee 94, 14195 Berlin, Germany. E-mail: pachur@mpib-berlin.mpg.de

[1]Note that our distinction between "affect-rich" and "affect-poor" choices and outcomes is an ordinal rather than an absolute one. Even affect-poor outcomes are not completely devoid of affective quality.

Pachur et al. fitted CPT's weighting function to the *aggregate* choices of their participants. Consistent with Rottenstreich and Hsee's proposal, they indeed found a more strongly inverse S-shaped function in affect-rich relative to affect-poor choices (see also Petrova et al., 2014). However, Pachur et al. could not rigorously test (because of the small number of choices for each individual) whether people classified as relying on the minimax rule would in fact be better described by CPT with strongly nonlinear decision weights. Moreover, parameter estimations on the aggregate level may mischaracterize the processes occurring on the individual level (e.g., Estes & Maddox, 2005). It is therefore unclear to what extent the Pachur et al. probability-weighting analysis captures individual choices.

In sum, there are two competing accounts of how the affect evoked by the imagery of outcomes impacts the cognitive mechanisms underlying risky choice. The available evidence has not allowed the two accounts to be rigorously pitted against each other. Whether people weight or ignore probabilities not only has theoretical implications (suggesting boundaries for the expectation framework); it also has practical implications for professionals communicating risks in highly affect-rich contexts, such as doctors or policy makers (see below).

In this article, our goals are twofold. First, drawing on a large number of decision problems, we fitted CPT's weighting and value functions to the choices of individuals. We then conducted a model comparison between CPT and the minimax rule to determine whether a given individual's affect-rich choices are better accommodated by pronounced nonlinear weighting of probabilities (Rottenstreich & Hsee, 2001) or by a strategy that shuns probabilities (Sunstein, 2002). Additionally, we considered—to our knowledge for the first time—the hypothesis that choices between options with adverse affect-rich outcomes give rise to a higher elevation of the weighting function than do choices between options with affect-poor outcomes, indicating more risk aversion. Rottenstreich and Shu (2004) proposed that decisions involving "affect-rich outcomes might give rise to more savoring (positive prizes) or dread (negative prizes)," which "would elevate the (absolute) value of affect-rich lotteries at every probability" (p. 454). As pointed out by Lopes (1995), a greater weight being assigned to the worst outcome of a lottery is associated with a higher degree of risk aversion (see also Abdellaoui, L'Haridon, & Zank, 2010; Birnbaum, 2008; Wakker, 2001).

Second, we addressed an important argument by McGraw, Shafir, and Todorov (2010), who suggested that systematic discrepancies between affect-rich and affect-poor choices stem from the different formats in which outcome information is presented. Affect-poor prospects have typically been presented in numerical format (i.e., monetary amounts) and affect-rich prospects in nonnumerical format (e.g., kisses, electric shocks; e.g., McGraw et al., 2010; Rottenstreich & Hsee, 2001; Shaffer & Arkes, 2009; but see Buechel et al., 2014; Nygren et al., 1996; Petrova et al., 2014). Because nonnumerical information may not lend itself to the straightforward integration of outcomes with probabilities, this format difference may prompt processing differences, including differences in the resulting weighting function. We examined this hypothesis in a condition in which the in the affect-rich outcome was presented alongside its montary value.

In order to systematically compare affect-poor and affect-rich choices, we used an experimental paradigm developed by Pachur et al. (2014). This approach allowed us to contrast choices involving different degrees of affect, while holding the options' monetary values constant. In the affect-rich domain, participants are presented with a (hypothetical) choice between two medications, each of which results in an adverse side effect (e.g., diarrhea, headache) with some probability. In the affect-poor domain, participants are presented with an isomorphic task in which each side effect is replaced by a monetary loss. To ensure that affect-poor and affect-rich prospects were monetarily comparable, we first asked each participant to indicate his or her subjective monetary valuation of each side effect (i.e., willingness to pay (WTP) to avoid each side effect). These individual-specific valuations were presented as monetary amounts (losses) in the affect-poor choices. In the affect-rich choice condition, half of the participants were presented with the side effect in combination with the respective WTP; the other half saw only the side effect. McGraw and colleagues (2010, Experiment 5) found that when participants were first asked to determine an item's monetary worth, in a subsequent valuation of a lottery involving the item they showed the same sensitivity to probabilities as in a valuation of a lottery involving a monetary outcome (note, however, that they used relatively affect-poor consumer items). In the monetary evaluation task of the Pachur et al. paradigm, participants also initially evaluated each outcome's WTP. However, this occurred early in the experiment and participants may thus no longer remember their stated WTPs once they reach the affect-rich choice task. The explicit presentation of WTPs alongside the medications' adverse effects therefore provides a clean test of the extent to which differences in format drive the discrepancy between affect-rich and affect-poor choice.

## WHAT ARE THE MECHANISMS UNDERLYING AFFECT-RICH AND AFFECT-POOR CHOICE?

### Method

#### *Participants*

Eighty-two students (59 women, aged 17–64 years, $M = 24.1$) participated for course credit in the study, which was conducted at the University of Basel. Participants were randomly assigned to each of the eight between-subjects conditions (see succeeding text).

#### *Materials*

Participants were presented with a total of four tasks: a monetary evaluation task, two choice tasks (involving affect-poor and affect-rich problems, respectively), and an affective evaluation task. In the *monetary evaluation task*, participants were first asked to rank the following 12 side effects from most to least unpleasant: fatigue, flatulence, diarrhea, fever, itching, trembling, dizziness, insomnia, depression, speech



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disorders, hallucinations, and memory loss. Participants then indicated their WTP (in Swiss Francs, Sfr) to avoid each side effect. Specifically, they were asked to imagine that they were suffering from an (unspecified) illness and needed to take medication for one week. Two medications were available. Both treated the illness equally well, but one was certain to have a specific side effect (e.g., insomnia) during the week of medication, whereas the other had no side effects. Participants indicated the additional amount they would be willing to pay to receive the medication without the side effect, relative to the medication with the side effect.

Next, participants were presented with *choice tasks*, one containing problems with affect-rich prospects; the other, affect-poor prospects. In the affect-rich task, participants chose between two medications, each leading to a particular side effect with some probability (e.g., medication A: insomnia with a probability of 15%; medication B: fever with a probability of 10%). In the affect-poor task, they chose between two monetary lotteries, each leading to the loss of an amount of money with some probability. We used each individual's WTP amounts to construct individualized affect problems that were monetarily equivalent to the affect-rich ones. Specifically, the affect-poor problems were drafted on the basis of the affect-rich problems, with the side effects being replaced by the individual-specific WTPs. To illustrate, let us consider a person who specified a WTP of 15 Sfr to avoid fever and 20 Sfr to avoid diarrhea. In the affect-rich choice task, she would choose between two medications, both equally effective in targeting a complaint, but with the possibility of different side effects: Medication A could cause fever with a probability of 15% (no side effects otherwise), and medication B could cause diarrhea with a probability of 10% (no side effects otherwise). In the corresponding affect-poor task, she would be presented with a choice between lottery A, leading to a loss of 15 Sfr with a probability of 15% (nothing otherwise), and lottery B, leading to a loss of 20 Sfr with a probability of 10% (nothing otherwise).

Participants were presented with two sets of 44 decision problems, one set representing affect-rich and the other set representing affect-poor problems. Each option in a problem contained one nonzero outcome. To better discriminate between CPT and the minimax rule, we constructed the affect-rich problems such that the two models would often make opposing predictions. Specifically, for 40 of the 44 problems, one medication implied a less severe but more probable side effect than the other. The probabilities were chosen such that the medication with the less severe side effect (which the minimax rule would choose) was the less attractive prospect according to CPT (to approximate participants' individual WTPs, we constructed the problems using the median WTPs for side effects obtained in a pilot study). In contrast to Pachur et al. (2014) and Pachur and Galesic (2013), we employed problems with intermediate but also very small and very large probabilities (e.g., .003 or .98) because CPT predicts extremely high sensitivity to differences in probabilities at the endpoints of the probability scale. In contrast, the minimax rule predicts no sensitivity to differences in probabilities. Finally, we ensured that the divergent predictions were robust across a large range of the CPT's probability sensitivity parameter, thus taking into account that participants may differ in their sensitivity to probabilities.[2] A full list of problems can be found in the supporting information.

Finally, participants completed a two-part *affective evaluation task*. First, each person was asked to imagine that she had lost a bet and would therefore lose a specified amount of money. For each of the monetary amounts she had indicated as WTPs, she now indicated on a scale from 1 (*not upset*) to 10 (*very upset*) the amount of negative affect she would experience if she had to pay this amount. Second, she was asked to imagine that she was required to take a medication and would experience a side effect. For each side effect, she indicated how upset she would feel if she experienced it.[3]

### *Design and procedure*

Participants first completed the monetary evaluation task before rendering choices in 44 affect-rich and 44 affect-poor problems. The order of the two blocks was counterbalanced across participants. In the affect-rich choice task, half of the participants were shown each side effect together with the respective WTP (it was highlighted that the value represented the participant's *individual* WTP). For instance, a participant might be presented with the following choice: Medication A could lead to fever (15 Sfr) with a probability of 15%; medication B could lead to diarrhea (20 Sfr) with a probability of 10% (no side effects otherwise). The other half of the participants saw only the side effects, without WTPs. In the affective evaluation task, we counterbalanced (across participants) whether the monetary amounts or the side effects were presented first.

Overall, we employed a $2 \times 2 \times 2 \times 2$ design, with the type of choice task (affect-poor vs. affect-rich) as a within-subjects factor and the order of affect-rich versus affect-poor choice task, the order of affect-rich versus affect-poor outcomes in the affective evaluation task (money vs. side effects), and the presence or absence of the respective WTP amounts in the affect-rich problem as between-subjects factors.

## Results

In the monetary evaluation task, fatigue was the side effect that triggered the lowest median WTP (12.5 Sfr) and memory loss triggered the highest (100 Sfr). The affective evaluations revealed a similar pattern, with the lowest average rating of 4.00 ($SD = 2.01$) for fatigue and the highest of 9.44 ($SD = 1.13$) for memory loss. This correspondence between monetary and affective evaluation also held on the individual level: Across participants, the average correlation between monetary and affective evaluations was high, $r = .88$, $t(80) = 5.87$ (one-sample $t$-test testing the mean Fisher's $z$-transformed correlation against zero), suggesting that participants' responses in the two evaluation tasks were quite

[2]The divergent predictions held across the range of 0.3–1 on the $\gamma$ parameter in CPT's probability weighting function (see Equation (3); with $\delta = 1$). For the value function represented in Equation (4), $\alpha = 1$.

[3]Specifically, the German term "sich ärgern" was used. It describes the state of being upset, angry, and annoyed.



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systematic. In Appendix A, we report detailed results for the monetary and affective evaluations, separately for each of the 12 side effects and the respective WTPs.

As expected, the side effects triggered stronger affective responses than the respective WTP amounts did, $M\text{s} = 6.32$ ($SD = 1.03$) vs. 5.66 ($SD = 1.42$), $t(81) = 3.96$, $p < .001$ (paired-sample $t$-test), consistent with our classification of choices between medications versus monetary losses as (relatively) affect-rich versus affect-poor, respectively.[4]

*Do choices differ between affect-poor and affect-rich lottery problems?*

Because our affect-rich and affect-poor problems were designed to be monetarily equivalent, they should, ceteris paribus, give rise to the same choices. Was this indeed the case? To find out, we tested whether the probability that participants chose the option with the higher expected value differed between affect-rich and affect-poor problems. Specifically, we conducted a mixed-effects linear modeling analysis with the glmer function in the lme4 package (Bates, Maechler, & Bolker, 2013) in R, with "participants" and "problems" as random intercepts and "affect condition" as a fixed effect and additionally as a random slope varying over participants (Barr, Levy, Scheepers, & Tily, 2013). The results showed that the likelihood of selecting the option with the higher expected value was 2.10 times higher for affect-poor problems than for affect-rich problems, $b = .744$, $CI_{95\%} = [.543, .947]$. This gap in choice (also observed in Pachur et al., 2014) resulted in a large proportion of preference reversals between corresponding affect-rich and affect-poor problems: Participants chose the same option in the affect-poor and affect-rich problems in only 54.7% ($SD = 18.1$) of cases.

*Does format make a difference?*

Using mixed-effects linear modeling (with "participants" and "problems" as random intercepts and "presence of WTP" as a fixed effect and additionally as a random slope varying over problems) focusing on the affect-rich choices, we found that the proportion of choices of the option with the higher expected value was not affected by whether side effects were supplemented with the respective WTP amounts in the affect-rich problems, $b = -.070$, $CI_{95\%} = [-.368, .228]$. Likewise, the proportion of preference reversals between affect-rich and affect-poor problems was not affected by the presence or absence of the WTP information, $U = 845.0$, $p = .963$. Thus, the discrepancy between affect-rich and affect-poor choices does not seem to primarily reside in differences in format.

*Computational modeling*

Next, we modeled participants' choices using CPT. According to CPT, in the two-outcome lotteries with only one nonzero outcome used in our studies, the valuation $V$ of lottery $A$ is determined as

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

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

$$v(x) = \begin{cases} x_i^{\alpha}, \text{if } x \geq 0 \\ -(-x_i)^{\alpha}, \text{if } x < 0 \end{cases} \tag{2}$$

The parameter $\alpha$ 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.[5] In Equation (1), $w(p_i)$ is the probability-weighting function that translates objective probabilities (Goldstein & Einhorn, 1987):

$$w(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma} + (1-p)^{\gamma}} \tag{3}$$

The parameter $\gamma$ 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 $\delta$ governs the elevation of the weighting function and can be interpreted as a measure of risk aversion (with $\delta > 0$; Gonzalez & Wu, 1999). As noted by Lopes (1995), a higher degree of risk aversion is linked to a greater weight being assigned to the worst outcome of a lottery (see also Abdellaoui et al., 2010; Birnbaum, 2008; Wakker, 2001). In a choice between two lotteries A and B, CPT predicts that the lottery with the more attractive $V$ is preferred.

To predict the choice probability $p(\text{A}, \text{B})$ of lottery A over B, we used the softmax choice rule:

$$p(\text{A}, \text{B}) = \frac{e^{\varphi \cdot V(\text{A})}}{e^{\varphi \cdot V(\text{A})} + e^{\varphi \cdot V(\text{B})}} \tag{4}$$

where $\varphi$ is a choice sensitivity parameter specifying how sensitive the choice probability is to differences in the valuations $V(\text{A})$ and $V(\text{B})$, computed according to CPT.

Our implementation of CPT involved four adjustable parameters: $\alpha$ for the value function, $\gamma$ and $\delta$ for the weighting function, and $\varphi$ for the choice rule. In accordance with CPT's main assumptions, we restricted the parameter values as follows for the estimation procedure (e.g., Scheibehenne & Pachur, 2015): $0 < \alpha \leq 1$; $0 < \gamma \leq 1$; $0 < \delta \leq 10$; $0 < \varphi \leq 10$. The deviation between the predicted and observed choices was quantified using the likelihood measure $G^2$, with a smaller $G^2$ indicating a better fit:

$$G^2 = -2\sum_{i=1}^{N} \ln[f_i(y|\theta)] \tag{5}$$

where $N$ refers to the total number of choices and $f(y|\theta)$ refers to the probability with which CPT, with a particular set of

[4]A reviewer suggested that one potential reason why monetary outcomes prompt weaker affective reactions than medical side effects is that the ultimate outcome (i.e., what is acquired with the money) is temporally more distant and uncertain.

[5]Because the decision 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.



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parameter values $\theta$, predicts an individual's choice $y$. That is, if option A was chosen, then $f(y|\theta) = p(\text{A,B})$ (with $p(\text{A,B})$ defined as in Equation (4)); if option B was chosen, then $f(y|\theta) = 1 - p(\text{A,B})$. In the estimation procedure, we first implemented a grid search. The 20 best-fitting sets of parameter value combinations emerging from the grid search were then used as starting points for subsequent optimization using the simplex method (Nelder & Mead, 1965), as implemented in MATLAB.

How well did CPT fit the choices made in affect-poor and affect-rich problems? Although choices in affect-rich problems had a worse average fit than those in affect-poor problems (see Table 1), the model fit of affect-rich choices was considerably better than chance (i.e., $G^2 = 61$, predicted under random choice).

How did the differences in participants' choices reported earlier translate into differences on CPT's parameters? Table 1 shows the average (across participants) parameter estimates for CPT (the median values show a very similar pattern), separately for affect-rich and affect-poor problems, and for the conditions with and without WTPs in the affect-rich choices. Furthermore, Figure 1 depicts CPT's weighting functions based on the average parameter values. As predicted by Rottenstreich and Hsee (2001), the sensitivity parameter ($\gamma$) was considerably lower for affect-rich than for affect-poor choices (see significance tests between conditions 1a vs. 1b and 2a vs. 2b in Table 1). This indicates that participants' affect-rich choices were less sensitive to probability information than their affect-poor choices were.

Furthermore, as predicted by Rottenstreich and Shu (2004), the elevation parameter $\delta$ was considerably higher in affect-rich problems. This suggests that participants were more risk averse in the affect-rich than in affect-poor choices. As indicated by the $\alpha$ parameter, CPT's value function was more strongly curved in the affect-poor than in the affect-rich problems, indicating higher sensitivity in the latter. Importantly, there were no differences in the best-fitting parameters as a function of whether or not the side effects were supplemented with numerical WTP information (see significance tests between conditions 1a vs. 2a and 1b vs. 2b in Table 1; Figure 1).

*Do affect-poor and affect-rich choices also differ within the same domain?*

In the analysis reported earlier, we distinguished between two domains that are, on average, relatively rich (medical treatments) versus relatively poor (monetary lotteries) in affect. However, the domains also differ in other respects (e.g., the object of choice: side effects versus monetary losses), thus rendering the interpretation of the differences observed in probability sensitivity and risk attitude as being due to differences in affect more difficult. To test the impact of affect more directly, we took advantage of the substantial variation in affect observed *within* each domain. For instance, higher monetary losses triggered stronger affect than smaller losses, and some side effects triggered stronger affect than others (Appendix A). Moreover, affective evaluations differed between participants, resulting in considerable

Table 1. Average Parameter estimates for cumulative prospect theory (CPT) obtained for choices in affect-poor and affect-rich problems, separately for the conditions with and without (numerical) willingness to pay (WTP) information in the affect-rich choice task, and results of significance testing for differences in estimates across the four conditions (for $G^2$, see text)

| | Experimental condition | | | | Significance tests of difference between conditions | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Without WTP | | With WTP | | 1a vs. 1b (within participants) | | 2a vs. 2b (within participants) | | 1a vs. 2a (between participants) | | 1b vs. 2b (between participants) | |
| CPT parameter | Affect poor (1a) | Affect rich without WTP (1b) | Affect poor (2a) | Affect rich with WTP (2b) | $t(41)$ | $p$ | $t(39)$ | $p$ | $t(80)$ | $p$ | $t(80)$ | $p$ |
| $\gamma$ | .49 (.22) | .34 (.31) | .49 (.25) | .35 (.33) | 2.64 | .011* | 2.34 | .025* | .00 | 1.00 | .19 | .846 |
| $\delta$ | 1.72 (2.11) | 5.58 (4.51) | 2.06 (2.51) | 4.45 (4.26) | 4.40 | <.001* | 3.11 | .003* | .66 | .511 | 1.17 | .247 |
| $\alpha$ | .32 (.33) | .49 (.40) | .31 (.30) | .63 (.40) | 1.98 | .054 | 4.00 | <.001* | .18 | .859 | 1.64 | .015 |
| $\varphi$ | 7.80 (3.71) | 3.70 (4.31) | 8.25 (3.21) | 4.16 (4.26) | 4.84 | <.001* | 4.80 | <.001* | .59 | .558 | .49 | .63 |
| $G^2$ | 24.99 (12.73) | 44.32 (12.21) | 24.34 (12.50) | 44.31 (11.34) | 8.34 | <.001* | 6.65 | <.001* | .23 | .816 | .00 | 1.00 |

Note: Affect-poor problems in conditions 1a and 2a were identical. Affect-rich problems in conditions 1b and 2b differed in whether WTP information was presented. Conditions 1a vs. 1b and 2a vs. 2b are within-participant comparisons, whereas 1a vs. 2a and 1b vs. 2b are between-participant comparisons. Standard deviations of the estimated parameters are in parentheses. $\gamma$ and $\alpha$ model the sensitivity to probabilities and outcomes, respectively, with higher values indicating higher sensitivity; $\delta$ gives the elevation, with higher values indicating higher risk aversion; $\varphi$ refers to the choice sensitivity, with higher values indicating higher sensitivity.

*Significant tests after applying a Bonferroni–Holm correction (Holm, 1979). With $m = 5$ tests within each comparison between two conditions, the observed $p$ values were first ordered in ascending order and then tested with $\alpha_1 = .05/m$, $\alpha_2 = .05/(m-1)$, …, $\alpha_j = .05/(m-(j-1))$.



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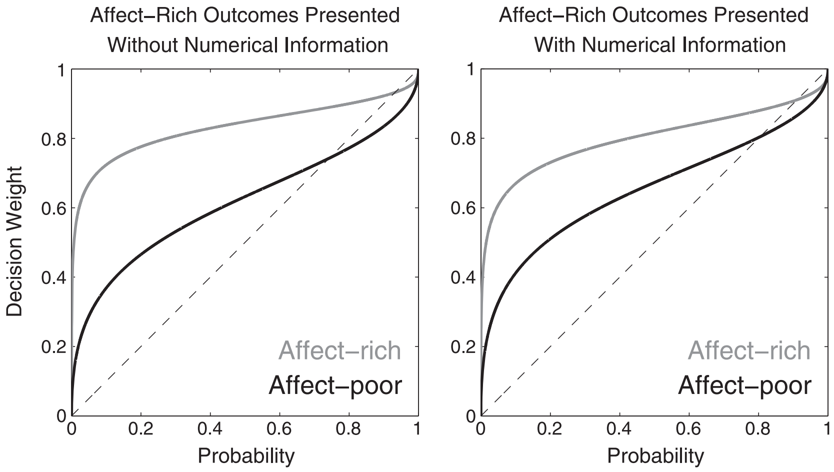


Figure 1. Cumulative prospect theory's weighting function, separately for affect-poor and affect-rich problems, and with numerical information absent (left panel) and present (right panel) in the affect-rich problems. Note that affect-poor problems were identical in both conditions. The two-parameter weighting function was fitted to choices, separately for individuals. The respective weighting functions based on the values averaged across individuals are shown

variability within the domains. If affect causes choices in affect-poor and affect-rich problems to diverge, then sensitivity to probabilities should also differ systematically within a domain.

We conducted an additional analysis in which affect-poor (affect-rich) problems were defined as those whose two outcomes had affect ratings lower (higher) than the median (6, across all participants) in the respective domain. This approach yielded two subsets of affect-poor problems (one with monetary outcomes, one with side effects) and two subsets of affect-rich problems. Because the presence or absence of numerical information in the choice problem with side effects barely affected parameter estimates in the earlier analysis, in this analysis we collapsed across the two affect-rich conditions. We then fitted CPT to the choices of each of the four subsets (aggregated across participants) to estimate probability sensitivity. As shown in Table 2 and Figure 2, probability sensitivity ($\gamma$ parameter) differed between choices in affect-poor and affect-rich prospects, irrespective of domain (i.e., monetary losses vs. side effects). Specifically, $\gamma$ was lower in the affect-rich subsets than in the affect-poor subsets for both the monetary problems, $\gamma = .23$ vs. .42, and the medical problems, $\gamma = .22$ vs. .29.

Table 2. Cumulative prospect theory's parameters in affect-rich and affect-poor problems within the problems with side effects vs. monetary losses (for $G^2$, see text)

| Class | | Type of outcome: Side effect | Type of outcome: Monetary loss |
|---|---|---|---|
| Affect rich | $\gamma$ | .22 | .23 |
| | $\delta$ | 10.00 | 1.71 |
| | $\alpha$ | .17 | .11 |
| | $\varphi$ | 1.90 | 10.00 |
| | $G^2$ | 1362.8 ($n = 1019$) | 449.2 ($n = 787$) |
| | Affect rating | >6 | >6 |
| | Median outcome | –99.5 | –200 |
| Affect poor | $\gamma$ | .29 | .42 |
| | $\delta$ | 1.98 | 1.48 |
| | $\alpha$ | .12 | .14 |
| | $\varphi$ | 2.60 | 4.51 |
| | $G^2$ | 942.0 ($n = 710$) | 1172.6 ($n = 1095$) |
| | Affect rating | <6 | <6 |
| | Median outcome | –23 | –15 |

Note: Because the value of $G^2$ depends on the number of problems included, these numbers are reported for each of the categories. $G^2$ under guessing was, for the side effects, 1412.6 (affect-high) and 984.3 (affect-low); for the monetary outcomes, 1091.0 (affect-high) and 1518.0 (affect-low). $\gamma$ and $\alpha$ model the sensitivity to probabilities and outcomes, respectively, with higher values indicating higher sensitivity; $\delta$ gives the elevation, with higher values indicating higher risk aversion; and $\phi$ refers to the choice sensitivity, with higher values indicating higher sensitivity.

*Do affect-rich lotteries evoke a different cognitive mechanism?*
One way to interpret CPT's worse model fit in affect-rich relative to affect-poor choices (i.e., $G^2$, Table 1) is that the premise of a multiplicative trade-off between outcomes and probabilities (as implemented by CPT) holds less for affect-rich choices. Moreover, as mentioned earlier, the higher elevation of the weighting function in affect-rich choices (indicating stronger risk aversion) suggests that greater weight is assigned to the worst outcome in this context (Gonzalez & Wu, 1999), consistent with the minimax rule. We next examined—using CPT rather than the expected-value strategy used by Pachur et al. (2014)—to what extent affect-rich prospects indeed trigger a qualitatively different cognitive mechanism than do affect-poor ones.

We conducted a model comparison involving CPT and the minimax rule. Specifically, we determined how well CPT (based on the estimated parameter values) and the minimax rule accounted for each individual participant's choices. To this end, we first computed each model's $G^2$, separately for individuals. The computation of a model's $G^2$ requires specification of the likelihood with which the model predicts an observed choice (Equation (5)). For the minimax rule, $G^2$ was calculated using the same choice rule as for CPT (Equation (4)), but with the valuations defined as $V(\mathrm{A}) = x_\mathrm{A}$ and $V(\mathrm{B}) = x_\mathrm{B}$, respectively. The minimax rule thus has one adjustable parameter (i.e., the choice sensitivity parameter



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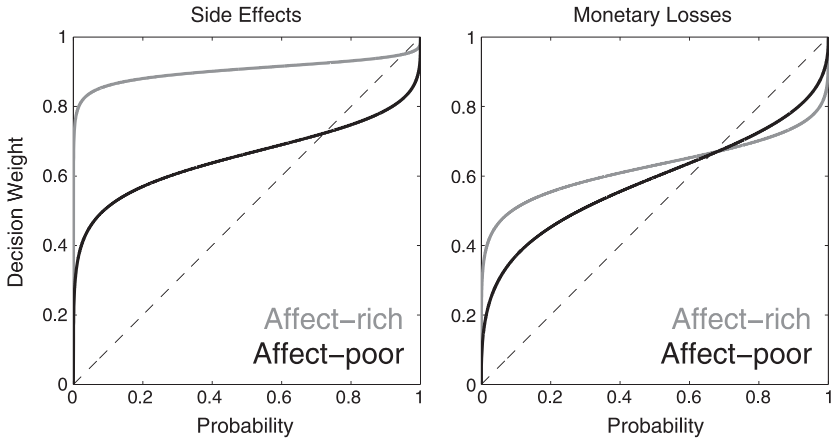


Figure 2. Cumulative prospect theory's weighting function, separately for choice domain (medical side effects versus monetary losses) and for affect-poor and affect-rich problems within each domain (see text)

in the choice rule), whereas CPT has four. In order to correct for differences in model flexibility, we evaluated the models with the Bayesian information criterion (BIC; Schwarz, 1978). BIC penalizes a model as a function of its number of adjustable parameters and is computed as follows:

$$BIC_M = G^2{}_M + k_M \times \ln(N) \tag{6}$$

where $k_M$ is the number of adjustable parameters for model $M$ and $N$ refers to the total number of choices. The smaller the $BIC_M$, the better a model fares. We determined model fits separately for affect-poor and affect-rich problems and for each individual. People were then classified according to the model with the lowest BIC. When the BIC exceeded that of a baseline model predicting a constant choice probability of .5, a person was designated as "unclassified" (in the respective class of problems).

We first examine the results for the condition with no numerical information in the affect-rich problems. Figure 3A plots the percentage of participants whose choices were consistent with CPT, with the minimax rule, or unclassified. The distribution differed considerably between affect-poor and affect-rich problems, $\chi^2(2, N=42)=39.92$, $p<.001$. In the former, most participants were classified as following CPT (95%); none as following the minimax rule; and 5% as unclassified. In affect-rich problems, the composition changed drastically: Nearly a third of participants were classified as following the minimax rule (31%; $z=6.06$, $p<.001$) and only 29% as following CPT ($z=9.61$, $p<.001$); and 40% remained unclassified. As a measure of classification reliability, we computed a Bayes factor for each classification. The Bayes factor is defined on the basis of the BIC differences between the best-fitting and second best-fitting models, $BF = e^{-\frac{1}{2}\Delta BIC}$ (Wasserman, 2000). This expresses how much more likely the data are under the assumption of the best as opposed to the second-best model. A Bayes factor in the range of 3 to 10 gives moderate evidence for the classification; a Bayes factor larger than 10, strong evidence. For affect-poor problems, the median Bayes factor for participants classified as following CPT was 41 355. For affect-rich problems, the median Bayes factors for participants classified

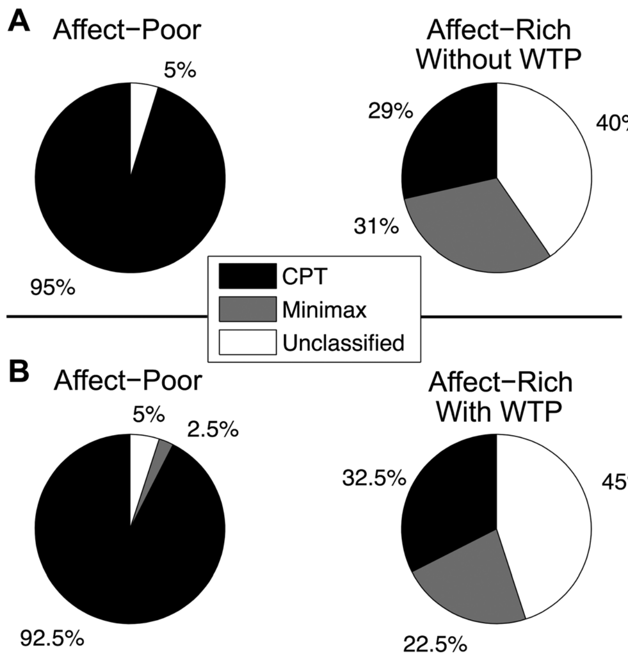


Figure 3. Participants classified as adhering to cumulative prospect theory (CPT), the minimax rule, or unclassified, separately for the affect-poor (monetary losses) and affect-rich (medical side effects) domain and with (A) or without (B) numerical information in the affect-rich domain (i.e., side effects only vs. side effects alongside their willingness to pay (WTPs)). Note that participants in the conditions with and without numerical information (between-subject design) responded to the same problems

as following CPT and the minimax rule were 10.09 and 6.09, respectively, indicating moderate to strong evidence.

Did the strategy classification differ when numerical information was provided in the affect-rich problems? Figure 3B plots the resulting classification. Irrespective of whether side effects were supplemented with WTP information, the pattern was very similar: in affect-rich problems, 29% vs. 32.5% for CPT ($z=.61$, $p=.54$) and 31% vs. 22.5% for minimax ($z=1.27$, $p=.20$); in affect-poor problems (which were identical in both conditions), 95% vs. 92.5% for CPT ($z=.60$, $p=.55$) and 0% vs. 2.5% for minimax ($z=.98$, $p=.33$). As a measure of classification confidence,



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we again computed a Bayes factor for each classification. In the conditions in which affect-rich problems were supplemented with WTP information, the median Bayes factors for affect-poor problems were 193 340 (CPT) and 697.97 (minimax rule). For affect-rich problems, the respective median Bayes factors were 70.93 and 10.17.[6]

## DISCUSSION

What cognitive mechanisms do affect-rich problems trigger, relative to affect-poor problems? Using CPT as a computational model, we found that choices in problems with affect-rich outcomes (medical side effects) were accommodated in terms of a more strongly inverse S-shaped probability-weighting function, indicating less sensitivity to probabilities (Figure 1). Moreover, affect-rich choices resulted in a higher elevation of the weighting function, indicating higher risk aversion. We conducted a model comparison between CPT and the minimax rule and tested both models on the level of individuals. In affect-poor problems, the large majority of individuals were best described by CPT; in affect-rich problems, the proportion of participants best described by the minimax rule was considerably higher (Figure 3). This pattern of findings suggests a qualitative difference in cognitive mechanisms. Specifically, affect-rich outcomes appear to recruit a simple strategy that embodies probability neglect in some people (but not everybody). This finding is consistent with process-tracing data reported by Pachur et al. (2014; Study 3), showing that people pay less attention to probability information in affect-rich than in affect-poor problems (see also Lejarraga, Pachur, Frey, & Hertwig, in press); as well as with a neuroimaging study by Suter, Pachur, Hertwig, Endestad, and Biele (2015). Admittedly, the outcomes in the affect-rich and affect-poor conditions differed not only in affect but, for instance, also in format, and the WTPs may not represent the participants' valuation of the side effect perfectly. The differences in choice between the conditions thus cannot unambiguously be attributed to affect. Therefore, it is important that we found that people's choices diverged regardless of whether side effects were presented alongside numerical information (i.e., WTP amounts; Figure 1), and that a difference in probability sensitivity similar to that between monetary losses and side effects (indicated by the $\gamma$ parameter) also emerged *within* each domain of problems (Figure 2), as a function of the degree of affect elicited by each problem.

## MODELING THE IMPACT OF AFFECT ON CHOICE: MULTIPLE MECHANISMS OR A DUAL SYSTEM?

In our strategy classification analysis, we modeled participants' choices using two approaches, CPT and the minimax rule. A number of participants, however, could not be classified (Figure 3). Might the distinction between the two approaches be too crude? Mukherjee (2010) recently proposed a formalized a dual-system model (DSM) approach for risky choice. This hybrid modeling framework assumes that risky choices stem from a confluence of two qualitatively different systems, whose relative influence can vary continuously: (i) a deliberate, expectation-based system that is sensitive to both outcome and probability information; and (ii) an affective system that is influenced by the decision maker's mood and how she feels about a specific prospect and that considers only the value of an outcome and whether it is possible or impossible (thus ignoring probability). The weight given to each system is governed by an adjustable parameter $w$. More formally, the subjective valuation of a lottery $A$ is defined as

$$V(\mathrm{A}) = w\frac{1}{n}\sum_{i=1}^{n} x_i^{\alpha} + (1-w)k\sum_{i=1}^{n} p_i x_i \tag{7}$$

where $n$ represents the number of the option's outcomes, and $p$ and $x$ the probabilities and the outcomes, respectively; $\alpha < 1$ models the decreasing sensitivity to the magnitude of the outcomes in the affective system (similar to CPT's value function; Equation (2)); and $k$ is a scaling constant that permits the deliberate system to scale the expected value of a lottery. Mukherjee proposed that the higher the contribution of the affective system (and hence the value of $w$), the more pronounced the affective nature of the outcomes.

The DSM approach allows for a varying confluence (governed by $w$) of two processes: one process similar to the one assumed by minimax (note that minimax does not assume decreasing sensitivity to the magnitude of outcomes) and one process assuming perfect probability sensitivity. Might this model account for participants' choices better than CPT and the minimax rule? To answer this question, we used the fitting procedure described earlier to estimate the parameters of the DSM for each person, separately for affect-poor and affect-rich problems. The DSM showed a very similar fit across the two problem domains, as indicated by the $G^2$ (Table 3). In both domains, the fit was substantially better

Table 3. Average parameter estimates for the dual-system model (DSM) obtained for choices in affect-poor and affect-rich problems and results of significance testing for differences in estimates

| DSM parameter | Lottery problem | | Significance tests | |
|---|---|---|---|---|
| | Affect poor | Affect rich | $t$-value | $p$ |
| $w$ | .20 (.38) | .44 (.42) | 3.75 | <.001* |
| $\alpha$ | .05 (.17) | .62 (.45) | 10.33 | <.001* |
| $k$ | 4.97 (3.88) | 2.75 (3.59) | 3.93 | <.001* |
| $\varphi$ | 1.33 (3.26) | 2.50 (3.57) | 1.34 | .18 |
| $G^2$ | 49.13 (10.30) | 49.21 (10.26) | 0.06 | .95 |

Note: Standard deviations of the estimated parameters are in parentheses. $w$ models how much weight is given to each system; $\alpha$ models the sensitivity of the affective system to outcomes, with higher values indicating higher sensitivity; $k$ is a scaling constant; and $\varphi$ refers to the choice sensitivity, with higher values indicating higher sensitivity.
*Significant tests after applying a Bonferroni–Holm correction (Holm, 1979). With $m = 5$ tests, the observed $p$ values were first ordered in ascending order and then with $\alpha_1 = .05/m$, $\alpha_2 = .05/(m-1)$, …, $\alpha_j = .05/(m-(j-1))$.

[6]Whether participants first answered affect-rich or affect-poor problems did not seem to influence their strategy selection in the subsequent task: the proportion of participants classified as following CPT, the minimax, or as guessing was comparable across the two conditions, $\chi^2(2, N = 82) = 1.87$, $p = .393$.



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than expected by chance. Further, the difference in the estimated $w$ parameters indicated that the affective system is given substantially more weight in affect-rich problems than in affect-poor problems, $w = .44$ vs. .20. To our knowledge, this result represents the first support for Mukherjee's (2010) hypothesis that choices involving affect-rich versus affect-poor prospects may differ in terms of the weight given to the different systems.

We next conducted a model comparison involving CPT, the minimax rule, and the DSM, again using the procedure described earlier (and again across all 82 participants). We determined separately for affect-rich and affect-poor problems how well CPT, the minimax rule (both based on the estimated parameter values), and the DSM (based on four individually estimated parameter values) accounted for each participant's choices. Figure 4 shows the results. The DSM model did not capture participants' choices better than the minimax rule or CPT, nor did it reduce the number of unclassified participants. To conclude, the DSM model did capture the differences between problem domains. Yet, in our choice set, it was not able to model choices better than when assuming the operation of two discrete mechanisms.

### Affect and strategy selection

The research programs on the adaptive decision maker (Payne, Bettman, & Johnson, 1993) and on simple heuristics (Gigerenzer, Hertwig, & Pachur, 2011) have both emphasized the contingent nature of human decision making and argued that people are able to select between different cognitive strategies. Environmental and task properties conducive to the use of particular strategies have been identified. For instance, it has been shown that simple, noncompensatory heuristics are more likely to be employed when attributes are highly intercorrelated (Bettman, Johnson, Luce, & Payne, 1993; Dieckmann & Rieskamp, 2007), when time is limited (Pachur & Hertwig, 2006; Payne et al., 1993), when information search is costly (e.g., Bröder & Schiffer, 2003; Hilbig, Michalkiewicz, Castela, Pohl, & Erdfelder, 2015), when cognitive resources are limited (e.g., Horn, Pachur, & Mata, 2015), in expert judgment (e.g., Pachur & Marinello, 2013), when the choice set involves many alternatives (Ford, Schmitt, Schechtman, Hults, & Doherty, 1989), and when conflict between alternatives is high (Pachur, Hertwig, Gigerenzer, & Brandstätter, 2013). Our results add to this list

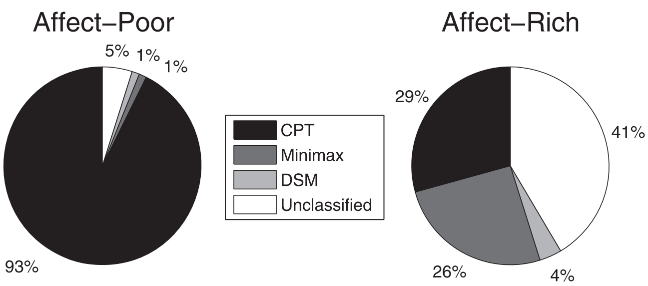


Figure 4. Participants classified as adhering to cumulative prospect theory (CPT), the minimax rule, the dual-system model (DSM), or unclassified, separately for affect-poor (monetary losses) and affect-rich (medical side effects) problems

of factors. Beyond statistical properties of the stimuli and contextual factors (e.g., time pressure), strategy selection may also be a function of the degree to which the problem evokes an affective response.

### Theoretical and practical implications

On a theoretical level, our findings suggest that models assuming expectation maximization may fail to accurately predict people's choices in the context of affect-rich outcomes. Instead, alternative modeling frameworks (e.g., lexicographic or one-reason decision making heuristics) may be more appropriate. On a practical level, the implication to be drawn from our findings is that—to the extent that people are less sensitive to probabilities (or neglect them altogether) in choices involving affect-rich outcomes—different decision aids may be required to facilitate good choices (see also Pachur, Hertwig, & Steinmann, 2012). For instance, professionals who communicate risks, such as doctors or policy makers, may guide people's attention to probability information by providing audience-tailored visualizations of the pertinent probabilities (Spiegelhalter, Pearson, & Short, 2011).

### Limitations

In what follows, we discuss three possible limitations of our experimental and modeling approach, beginning with the employed measure of affect. We gauged the amount of affect a side effect or a monetary loss evoked by asking participants how upset they would be if they experienced it. Yet "being upset" may tap into the affective pool associated with an outcome but fail to characterize the multidimensionality of the sum of all affective responses. To find out how good a proxy our "being upset" measure is, we conducted an additional study in which we correlated reported degrees of "upset" about the same side effects and monetary losses employed in the present study with individuals' overall affective responses. The latter were measured by assessing participants' responses on seven basic emotions (Ekman, Friesen, & Elsworth, 1982) and computing a total affect score (separately for each participant and each item). We found that the "being upset" ratings correlated very highly with the general affect score for both the side effects (average $r = .85$, $p = .003$) and the monetary losses (average $r = .91$, $p = .001$; one-sample $t$-tests testing the mean Fisher's $z$-transformed correlation against zero).[7] Nevertheless, it is clear that future investigations need to shed further light on what exactly causes a stimulus to be rich in affect, and which attributes of an event, an object, or an experience elicit what kind of affects (e.g., basic emotions).

Another possible limitation concerns the difference in format between side effects and their monetary equivalents (WTPs). When participants were asked to assign to each side effect a monetary value, the side effects were presented in relatively abstract terms (e.g., fatigue during the week of

[7]Detailed results and study procedures can be found in the Supporting Information.



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medication), thus leaving it to each person to specify the intensity of the experience (from slight to debilitating). Admittedly, this may have amplified individual differences in valuations and possibly made them less reliable. However, let us point out that such interpretative differences, if and to the extent that they occurred, and resulting variability in WTPs do not undermine our conclusion regarding differences between affect-rich and affect-poor choice. The reason is that we used individual-specific monetary lotteries, that took into account each individual's interpretation of the experience. Thus, for each individual, we compared affect-rich (side effects) and "personalized" affect-poor (monetary losses) stimuli. Furthermore, in the condition in which WTPs were explicitly presented alongside the potential side effects, we gave respondents the exact WTPs they reported on the basis of their subjective evaluations of the side effects. In this condition, both the monetary outcomes and the side effects were thus quantified precisely. Similarly, note that in the analysis showing reduced probability sensitivity in affect-rich choices also *within* the side effects domain and *within* the monetary domain (Figure 2 and Table 2), the affect-rich and affect-poor outcomes are described in the same format.

Further, the elicited WTP responses may be a noisy measure of a person's actual evaluations of side effects, making it difficult to model people's choice in the affect-rich condition using these WTPs as proxies for outcome information. In fact, this may explain both why the proportion of unclassified participants was considerably higher in the affect-rich than in the affect-poor choices and why the difference in the probability sensitivity parameter in the within-domain analysis was larger for affect-poor choices (Table 2)—the basis for the modeling might have been less noisy there. It is unlikely, however, that this lack of reliability compromises our conclusion that the probability sensitivity was reduced in affect-rich choice. First, Pachur and Galesic (2013) found no association between the reliability of WTP responses (elicited twice for each participant) and the gap between affect-rich and affect-poor choices. Second, it is unclear how a lack of reliability of the outcome information should lead to the observed differences in probability sensitivity.

Finally, a substantial portion of participants could not be classified in our modeling analysis. We can think of three possible reasons. One is the aforementioned lack of reliability of the WTP responses. A second possibility is that more participants resorted to guessing in affect-rich problems when faced with the requirement to trade off nonnumerical outcomes and numerical probabilities. However, the proportion of unclassified participants was equally high in affect-rich problems with and without WTP information (Figure 3). Third, it is, of course, possible that numerous participants recruited another strategy altogether or relied on a blend of different strategies (but see the previous section on modeling a dual-system account).

A potential boundary condition of our conclusions resides in our focus on the loss domain. Do our findings generalize to gains? Using a similar experimental procedure as employed here, Pachur et al. (2014) compared affect-rich and affect-poor choices in loss and gain domains. The same key results emerged across both domains: (i) higher affective evaluations of nonmonetary outcomes than of their monetary equivalents; (ii) a substantial and systematic discrepancy in choices between affect-rich and affect-poor problems; and (iii) evidence of probability neglect in affect-rich choices (see also Nygren et al., 1996). Relatedly, Rottenstreich and Hsee (2001) also found evidence for reduced sensitivity to probabilities in both negative and positive affect-rich outcomes (an electric shock vs. a coupon for a summer vacation in Europe). Nevertheless, one obvious question for future research is to what extent the phenomenon of probability neglect (as implemented by the minimax rule) hinges on statistical properties of the options, such as dominance (e.g., Brandstätter et al., 2006) or widely varying probabilities.

### Mechanisms in affect-poor risky choice

In our analysis, we entered CPT in the model competition because this model and one of its core components, probability weighting, has featured prominently in accounts of how affects shape risky choice (e.g., Rottenstreich & Hsee, 2001). Moreover, CPT has been shown to describe numerous violations of expected utility theory (but see Birnbaum, 2008) and to map individual differences (Glöckner & Pachur, 2012; Pachur et al., 2010). Let us emphasize, however, that Suter, Pachur, and Hertwig (2013) have demonstrated by means of computer simulations that—despite starkly different algorithmic structures—CPT can accommodate heuristic-based choices with a good model fit. This means that our results do not exclude the possibility that the large majority of participants in affect-poor problems who are well captured by CPT relied on heuristic principles rather than on an expectation-based calculus. In fact, process analyses of risky choice in the monetary domain have provided evidence for heuristic processes (such as limited and intradimensional search; e.g., Pachur et al., 2013; Rao, Li, Jiang, & Zhou, 2012; Rao et al., 2011; Su, Rao, Sun, Du, Li, & Li, 2013; Venkatraman, Payne, & Huettel, 2014). Therefore, our result that cognitive mechanisms appear to be altered qualitatively (e.g., one-reason decision making) rather than quantitatively (different degree of probability weighting) when affect enters the picture (at least for some respondents) should be extended in future research to understand more precisely the cognitive mechanisms in affect-poor risky choice.

## CONCLUSION

We used computational modeling to investigate how the nature of risky choice changes when outcomes evoke affects. With affect-rich outcomes, we found that individuals' sensitivity to probability information is attenuated, as suggested by a more strongly inverse S-shaped probability-weighting function. One explanation is that some participants appear to apply a strategy—accommodated by the model of the minimax rule—that ignores probabilities altogether. They do so even when the affect-rich problems are supplemented with numerical information about the outcomes. One task ahead is to further unpack this apparent impact of affect on



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## APPENDIX A

Table A1. Monetary equivalents (i.e., WTP) of the affect-rich outcomes (obtained in the monetary evaluation task) and affect ratings of the affect-rich outcomes and their monetary equivalents (on a 1–10 scale)

| | Monetary equivalents (in Swiss Francs) | | | Affect ratings | | |
|---|---|---|---|---|---|---|
| | Percentile | | | | | |
| Side effect | 5% | 50% | 95% | Side effects *M* (*SD*) | Monetary equivalents *M* (*SD*) | 95% CI of difference |
| Fatigue | 1 | 12.5 | 850 | 4.00 (2.01) | 3.64 (2.37) | [–.13, .86] |
| Flatulence | 4 | 15 | 255 | 4.15 (2.14) | 3.40 (1.89) | [.35, 1.15] |
| Trembling | 3 | 20 | 975 | 4.54 (2.20) | 3.91 (2.25) | [.15, 1.10] |
| Itching | 5 | 30 | 182.5 | 4.55 (2.07) | 4.26 (2.02) | [–.16, .74] |
| Diarrhea | 4.5 | 27 | 1150 | 4.89 (2.01) | 4.41 (2.19) | [–.04, .99] |
| Fever | 5 | 32.5 | 1500 | 5.11 (1.83) | 4.90 (2.35) | [–.32, .74] |
| Insomnia | 10 | 50 | 3350 | 6.44 (2.05) | 6.15 (2.27) | [–.26, .84] |
| Dizziness | 13.5 | 50 | 4749.5 | 7.03 (1.91) | 6.30 (1.94) | [.19, 1.26] |
| Hallucinations | 12.5 | 86.5 | 4950 | 8.23 (2.12) | 7.49 (2.10) | [.33, 1.14] |
| Speech disorders | 15.5 | 79 | 7500 | 8.44 (1.71) | 7.45 (2.10) | [.55, 1.42] |
| Depression | 15 | 85 | 5250 | 9.01 (1.35) | 7.61 (2.10) | [1.00, 1.80] |
| Memory loss | 21 | 100 | 15000 | 9.44 (1.13) | 8.45 (1.75) | [.64, 1.34] |

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 ratings for their monetary equivalents (i.e., WTP).

information processing in risky decision making and to understand the potential costs and benefits.

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*Authors' biographies*:

**Renata S. Suter** received her PhD from University of Basel in 2012. She is currently an adjunct researcher at the Center for Adaptive Rationality at Max Planck Institute for Human Development in Berlin. Her research interests focus on the psychology of risky choice, the influence of affect on decision making, and moral decision making.

**Thorsten Pachur** is a senior researcher at the Center for Adaptive Rationality at Max Planck Institute for Human Development in Berlin. He studies learning and memory processes in decision making as well as strategy selection, using computational modeling and process analyses.

**Ralph Hertwig** is the director of the Center for Adaptive Rationality at Max Planck Institute for Human Development in Berlin. He held positions at University of Chicago and Columbia University and served as the chair for Cognitive and Decision Science and Dean of Research at University of Basel.

*Authors' address*:

**Renata S. Suter, Thorsten Pachur and Ralph Hertwig**, Max Planck Institute for Human Development, Berlin, Germany.



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