SUPPLEMENT

Emotion and Decision-Making Under Uncertainty: Physiological arousal predicts increased gambling during ambiguity but not risk

Running Title: Emotional arousal and decisions of uncertainty

Oriel FeldmanHall[a], Paul Glimcher[b], Augustus L Baker[a], Elizabeth A Phelps[a,b,c]

[a]Department of Psychology, New York University, New York NY 10003
[b]Center for Neural Science, New York University, New York NY 10003
[c]Nathan Kline Institute, Orangeburg, NY 10962

SUPPLEMENTAL METHODS

Participants. Sample size was determined from past work using the same task (Tymula et al., 2012). Five subjects were not included in the analysis for the following reasons: two participants were excluded for failing to understand the task during debriefing and their SCR and behavioral data was subsequently never scored, and an additional three participants were not included because of technical difficulties, or for failing to exhibit any skin conductance response during the initial test phase which required participants to hold their breath (see section on skin conductance response for more details).

Task. Participants completed a computerized lottery task consisting of 62 trials, adapted from Tymula and colleagues (Tymula et al., 2012). Each lottery depicted a stack of 100 red and blue poker chips (Fig 1A). The lotteries corresponded to actual bags filled with red and blue chips placed in the testing lab and which were used to pay participants (see Table S1 for full list of choice types, which were evenly presented across the task, 3.2% choice proportions). The color associated with winning the monetary reward was counterbalanced, as was the side the lottery option was presented. Risky trials were always presented as 25%, 50%, or 75% probability of winning. During ambiguous trials, the probabilities were occluded to varying degrees. For example, during an ambiguous trial, participants could face a sure $5, or a lottery paying $20 or $0 with a gray occluder covering 50 of the poker chips. Thus, the participant knows there are at least 25 red and 25 blue chips, but the remaining 50 can be any combination of red and blue, implying that the odds of winning $20 can be anywhere from 25% to 75%. Occluder size ranged from 24% (low ambiguity) to 74% (high ambiguity). As recent data suggests that risk and ambiguity preferences are stable across the loss and gain domain—e.g. aversion to uncertainty is a constant preference and is greater in the loss than gain domain—(Tymula, Belmaker, Ruderman, Glimcher, & Levy, 2013), we only examined risk and ambiguity within the gain domain. Lotteries were presented for a fixed 6 seconds, at which time a green button appeared cuing the participant to key in their response. Participants had up to 3.5 seconds to make a response. Once a response was recorded, participants viewed a schematic of which button they pressed, providing visual feedback of the choice they made (presented for 1 second). The inter-trial-interval was a jittered fixation cross presented for 4-6 seconds.

TABLE S1: All possible choice types.

RISK	***AMBIGUITY***
Risk 25% $5	Ambiguity 24% $5
Risk 25% $8	Ambiguity 24% $8
Risk 25% $20	Ambiguity 24% $20
Risk 25% $50	Ambiguity 24% $50
Risk 25% $125	Ambiguity 24% $125
Risk 50% $5	Ambiguity 50% $5
Risk 50% $8	Ambiguity 50% $8
Risk 50% $20	Ambiguity 50% $20
Risk 50% $50	Ambiguity 50% $50
Risk 50% $125	Ambiguity 50% $125
Risk 75% $5	Ambiguity 74% $5
Risk 75% $8	Ambiguity 74% $8
Risk 75% $20	Ambiguity 74% $20
Risk 75% $50	Ambiguity 74% $50
Risk 75% $125	Ambiguity 74% $125

Payment. Given that research indicates that people behave differently when their choices are hypothetical (FeldmanHall et al., 2012; Holt & Laury, 2002), in this task, participants' choices were consequential. Participants were informed that at the end of the experiment, one trial would be randomly selected and their decision on that trial would result in real monetary consequences. The experimenters created a number of paper bags with lottery images that corresponded to those used in the task. The bags were filled with a number of blue and red poker chips proportional to the outcome probability stated by the lottery display. Following the task, each participant first drew a numbered poker chip from a separate paper bag to select a random trial for payment. If on the selected trial the participant chose to gamble, they played the lottery depicted in the trial by drawing a chip from the corresponding paper bag. If the participant drew a winning chip, they received a bonus payment equal to the value of the lottery (between $5 and $125); if they drew a losing chip they were not able to make additional money and were compensated $10 for participating in the study. If on the selected trial the participant chose the sure outcome, they received an additional $5 in compensation.

To ensure that participants understood the task and payout structure, at the end of the computer presented instructions, the experimenter always said: *"So I want to explain how payment works. As you can see, we have multiple bags lined up. Each bag has a picture that matches each lottery image used in the experiment. The outcome probabilities are stated here (point to bags). In other words, these pictures of the probabilities correspond to the options you will see during the experiment. Please make sure you understand this, as we will use these bags later to pay you out for one randomly selected lottery. To reiterate, you will be paid out based on your choices, and these bags will be used later to play randomly chosen trials for payoff. After the experiment, you will be allowed to look inside the bags to see that they match the stated probability or ambiguity level pictured here."*

Skin conductance response collection. Participants performed the task in a soundproof experiment room equipped with an MP-150 BIOPAC system used to record skin conductance responses (SCRs). Prior to the task, participants read through the instructions and practiced the task for 10 trials. At the start of the task, the experimenter attached the BIOPAC sensors to participants' left palm and instructed them to keep their arm as still as possible for the duration of the study in order to collect SCRs. The experimenter then performed two tests to ensure that SCR responses could be collected. After allowing a baseline SCR to develop, the experimenter instructed the participants to take a deep breath and hold it for three seconds in order to determine if adequate SCRs could be produced. For the second test, the experimenter asked participants to purse their lips and blow air as if they were inflating a balloon, but without releasing their breath. If one or both tests produced an adequate SCR response, the experimenter continued with the experiment, otherwise, the participant was compensated $10 and dismissed without completing the task. The experimenter remained in the room with the participants for the duration of the study to monitor their SCR recording and to transition them from block 1 to 2 of the task.

SCRs were recorded and analyzed using AcqKnowledge (version 3.7.3, BIOPAC Systems Inc.). The data was collected at 200 samples per second using a low pass digital filter with a 25 Hz cutoff frequency and a smoothing factor of 10 samples. SCRs were considered related to the choice if the base-to-peak response (i.e. SCR_{max} - SCR_{min}) was within the established window of .5s after the onset of the stimulus to .5s after the offset of the stimulus (10.5s total). Responses starting before .5s after the onset are unable to be considered elicited by the stimulus and were thus not analyzed (Dawson, Schell, & Filion, 2007). Threshold response criterion was set at .02 µvolts or greater and responses that failed to meet this criterion were scored as 0 (Dawson et al., 2007). Since raw SCRs follow a skewed distribution, SCRs were normalized by taking the square root of each score as commonly done in studies that measure electrodermal activity (Dawson et al., 2007), which allows for SCR data to be analyzed using parametric tests.

SUPPLEMENTAL RESULTS

Gambling behavior as a function of uncertainty type. We note that during ambiguous trials, even though increasing the occluder size reduces information about the lottery, the objective winning probability is always 50%. This is because red chips are the winning color in exactly half of the trials, and participants do not know whether a red or blue chip will be selected for play on any given trial (Ellsberg, 1961; Glimcher & Rustichini, 2004). In other words, all ambiguity lotteries had exactly 50 red chips and 50 blue chips regardless of the occluder size. Thus, an ambiguity-neutral person should view ambiguous lotteries as the same as risky lotteries with a 50% chance of winning. An extremely pessimistic, or ambiguity-averse individual would fear that the ambiguous offer in Fig 1B contains only 25 red chips and would treat this as a lottery with a 25% chance of winning. An extremely optimistic, or ambiguity seeking individual would behave as if there was a 75% chance of winning.

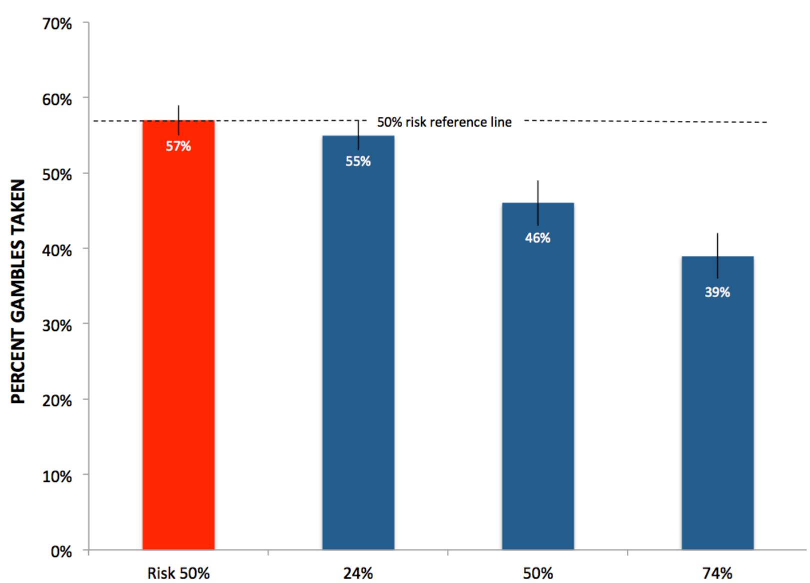

FIG S1 | A) *Despite all ambiguous lotteries containing 50% chance of winning the lottery, participants gambled less during ambiguous trials, indicating a greater aversion to ambiguity than risk.*

While participants gambled on 57% of trials where there was a known 50/50 chance of winning (50% risk, indicated by the dotted line in Fig S1), they took less gambles during trials that contained ambiguity. For example, trials with 50% ambiguity had a 46% endorsement rate and trials with 74% ambiguity had 39% endorsement rate, indicating that not only do individuals perceive ambiguous uncertainty as more aversive than risky uncertainty, but that increasing ambiguous uncertainty is mirrored by increasing aversion to taking the gamble.

MODEL SPECIFICATIONS

Descriptive Statistics of Model Parameters. Below we report the descriptive statistics of risk attitudes (alphas), ambiguity attitudes (betas), and the extracted subjective value (SV) across all participants.

TABLE S2: Population level descriptives of model parameters.

	Mean	SD	Min	Max
Alphas	.66	.27	.22	1.47
Betas	.42	.49	-1.02	1.43
SV overall	6.09	11.9	-1.14	89.07
SV Risk	6.4	11.4	.36	80.09
SV Ambiguity	5.77	10.9	-1.14	89.07

Choice and Subjective value. The subjective value of a lottery should inherently signal whether an individual will take the gamble, such that lotteries with higher subjective values will be chosen more often. That is, if our Gilboa and Schmeidler model is correctly indexing the parameters of the decision-space, then subjective value should accurately predict choice. To test if this were the case, we ran a trial-by-trial logistic regression using SV to predict probability of gambling. Critically, while we observed a robust positive relationship between higher SV and greater likelihood of gambling, there was no interactive effect between SV and uncertainty type (Table S3). Indeed, higher SVs were strongly coupled with increases in gambling behavior under both risky and ambiguous contexts (Table S4, Figs S2). This importantly reveals that our model has successfully taken into account an individual's sensitivity to risk and ambiguity. If the model had revealed different relationships between SV and choice as a function of uncertainty type, it would indicate that uncertainty attitudes (Alphas and Betas) are not good indexes of decisions under risk and ambiguity, respectively.

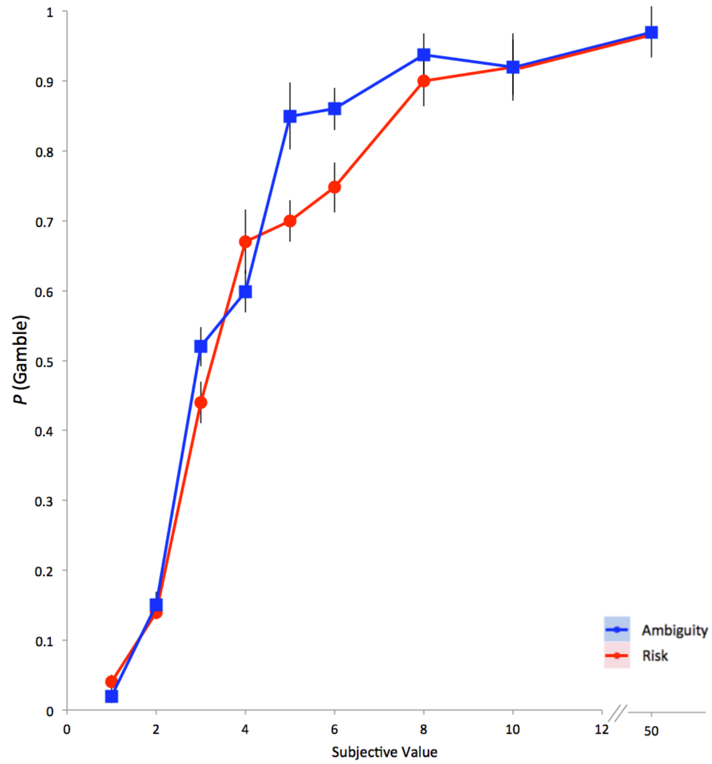

FIG S2| *Choice and Subjective Value. Probability of choosing the gamble based on uncertainty type and subjective value. Subjective Value is represented in bins of 1. Subjective value measurement's greater than 10 were collapsed into 1 bin. The corresponding Hierarchal logistical regression (Table S4) reveals that subjective value and deciding to take the gambling are intimately coupled, regardless of whether the context was risky or ambiguous. Error bars represent 1 SEM.*

TABLE S3: $Choice_{i,t} = \beta_0 + \beta_1 SV_{i,t} \times \beta_2 Uncertainty\,Type_{i,t}$

Choice ~ SV × Uncertainty Type; where SV is indexed by subject and trial, uncertainty type is an indicator variable for risk and ambiguity

	Coefficient (β)	Estimate (SE)	t-value	P value
Choice	Intercept	*-7.11 (.78)*	*-9.03**	*<0.001****
	SV	*2.76 (.33)*	*8.38**	*<0.001****
	Uncertainty Type	*-1.28 (.84)*	*-1.53*	*.12*
	SV*Uncertainty Type	*.23 (.32)*	*.71*	*.48*

AIC: 1363.3, Log Likelihood: -669.7

TABLE S4: $Choice_{i,t} = \beta_0 + \beta_1 SV_{i,t}$

Choice ~ SV; where SV is indexed by subject and trial, regressions done separately for risk and ambiguity

	Coefficient (β)	Estimate (SE)	t-value	P value
Choice	Intercept	*-8.23 (1.01)*	*-8.1*	*<0.001****
	Risk SV	*3.07 (.42)*	*7.2*	*<0.001****
	Intercept	*-7.43 (.98)*	*-7.5*	*<0.001****
	Ambiguity SV	*2.96 (.43)*	*6.9*	*<0.001****

For all reported regressions, terms were entered as both fixed and random effects (i.e. maximal models), risk was coded as 0, and ambiguity as 1; choice was coded with a 0 indicating no gamble (i.e. safe bet), and 1 indicating gamble. We used the glmfit function in MATLAB 2016a to run all regressions, and adhered to the maximal model framework denoted by (Barr et al., 2013). Choice regressions were fit using the laplace method with the logit link function.

Model Fits. To get an overall sense of how well our model fits choice behavior, we calculated the percentage of choices that are correctly predicted by the model. We first calculated the subjective value of the lottery and compared it to the subjective value of the reference choice (always \$5). If the subjective value of the lottery is higher than the subjective value of the reference choice, then our model indicates the participant should choose the lottery and not the reference choice. We compared the number of times the model correctly predicted choice based on this criteria. Our model predicts choice extremely well (Tables S5) on average (across all participants) 89% of the choices were correctly predicted across both risk and ambiguity. In only 4 subjects did the model fail to correctly predict choice at least 85% of the time. We did not find any difference in how well our model predicted choice between risky and ambiguous trials (logistic regression, $\beta = .079\ (.13)$, p=.56). Pseudo R2 was computed by (1-LL/LL0) where LL is the negative log likelihood and LL0 is calculated by sum((choice==1).*log(0.5) + (1 - (choice==1)).*log(0.5)).

TABLE S5: Gilboa & Schmeidler Model fits.

Population level model fits	Mean	SD	Min	Max
R^2	.76	.18	.22	1.0
LL	-9.8	7.6	-32.4	-.001
AIC	24.6	15.2	6.0	70.9

Percentage of choice correctly predicted by model	Mean	SD	Min	Max
Overall % of choices correctly predicted by model	88.7%	.14	43%	100%
Risk: % of choices correctly predicted by model	89.4%	.16	31%	100%
Ambiguity: % of choices correctly predicted by model	88.0%	.14	40%	100%

Alternative models

Expected Value Model. Given that individuals are known to be averse to uncertainty, informed decisions should not per se be considered synonymous with computing the expected value of a lottery. For example, if the expected value (EV) of a lottery is extremely high (and even if one computes this EV), because individuals can be averse to uncertainty, they may not take the gamble, even though the EV dictates they should (Holt & Laury, 2002). To test for the possibility that participants are making well-informed choices by calculating the expected value, we calculated each lottery's EV. While EV did predict choice (Table S6; AIC: 1689.6, Log Likelihood: -830.8), we found no evidence that there was an interaction with EV and uncertainty level. Furthermore, when we tested how well the EV model stood up against the subjective value (SV) model we found that the SV model did a significantly better job at predicting choice (model comparisons p<0.001; EV Model: AIC: 1332.7, Log Likelihood: -652). Indeed, the EV model correctly predicted choice only 76% of the time on risky trials and 71% on ambiguity trials, revealing an accuracy rate almost 20% worse than the SV model. This was also the case for models that examined the direct influence of monetary wins on choice (Table S7).

TABLE S6: $Choice_{i,t} = \beta_0 + \beta_1 EV_{i,t} \times \beta_2 Uncertainty\ Type_{i,t}$

Choice ~ EV$\times$ Uncertainty Type; where Expected value is indexed by subject and trial, uncertainty type is an indicator variable for risk and ambiguity

	Coefficient (β)	Estimate (SE)	t-value	P value
Choice	Intercept	*-3.79 (.48)*	*-7.84*	*<0.001****
	Expected Value (EV)	*.37 (.06)*	*5.46*	*<0.001****
	Uncertainty Type	*-0.41 (.45)*	*-0.89*	*.37*
	EV $\times$ Uncertainty Type	*.11 (.06)*	*1.80*	*.08*

AIC: 1689.6, Log Likelihood: -830.8

TABLE S7: $SCR_{i,t} = \beta_0 + \beta_1 Money_{i,t} \times \beta_2 Uncertainty\ type_{i,t}$

SCR ~ Money $\times$ Uncertainty Type; where Money is indexed by subject and trial (and has been z-scored), and uncertainty type is an indicator variable for risk and ambiguity

	Coefficient (β)	Estimate (SE)	t-value	P value
SCR	Intercept	*0.48 (.07)*	*7.2*	*<0.001****
	Money	*0.02 (.009)*	*2.9*	*0.006***
	Uncertainty Type	*-0.01 (.01)*	*-0.9*	*0.37*
	Money*Uncertainty Type	*-0.02 (.01)*	*-1.6*	*0.10*

***p<0.001, **p<0.01, *p<0.05

TABLE S8: $SCR_{i,t} = \beta_0 + \beta_1 Choice_{i,t}$

SCR ~ Choice $\times$ Uncertainty; where Choice is indexed by subject and trial, separately for risk and ambiguity

	Coefficient (β)	Estimate (SE)	t-value	P value
SCR	Intercept	*.48 (.06)*	*7.01*	*<0.001****
	Risky Choice	*-.03 (.03)*	*-0.9*	*0.38*

Intercept	*.45 (.06)*	*7.01*	*<0.001****
Ambiguous Choice	*.07 (.03)*	*2.4*	*0.02*

***p<0.001, **p<0.01, *p<0.05

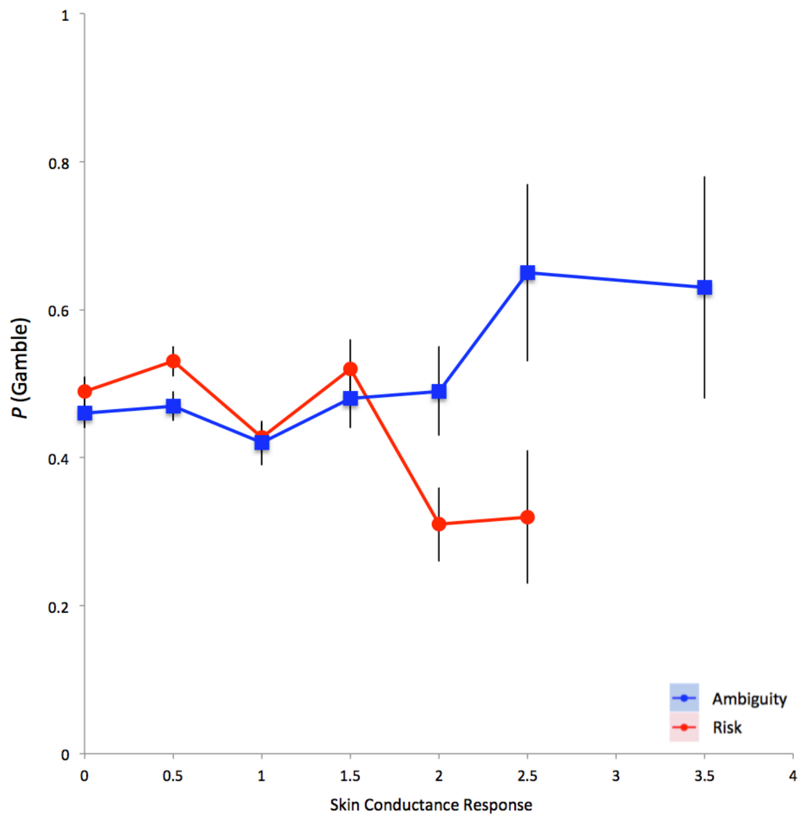

FIG S3 | *Emotional Arousal as a function of Choice During Ambiguity and Risk Contexts for all trials. A logistic regression predicting gambles as a function of SCR for risk and ambiguity, reveals that increasing emotional arousal predicts a greater likelihood of taking the safe option during risky trials, suggesting that arousal may serve as a safety signal in highly risky contexts. The opposite pattern of results was observed for Ambiguous trials. Unlike in Fig 4A, data is plotted for all risk and ambiguity trials, irrespective of uncertainty level. SCR is binned in .5 increments. Error bars represent 1 SEM.*

Emotional arousal strengthens the relationship between subjective value and choice for ambiguous uncertainty. To more precisely characterize the relationship between choice and SCR as a function of subjective value, a multi-level path model approach was employed for both risk and ambiguity. This model can test whether the behavioral relationship between gambling (Y) and subjective value (X) is statistically mediated by the arousal response (M). This approach can help further decompose whether the arousal response is mediating the relationship between subjective value (the subjective perception of how good the lottery is) and choice.

Results reveal no evidence of arousal mediating the relationship between SV and decisions to gamble during risky trials (indirect effect: 0.03, p=.80). In contrast, we observed that arousal acts as a suppressor during ambiguity trials (Fig S4, indirect effect: 0.12, p=0.04). That is, by including SCR into the regression equation, the predictive validity of SV on choice increased, indicating that the relationship between subjective value and gambling is strengthened by the arousal response.

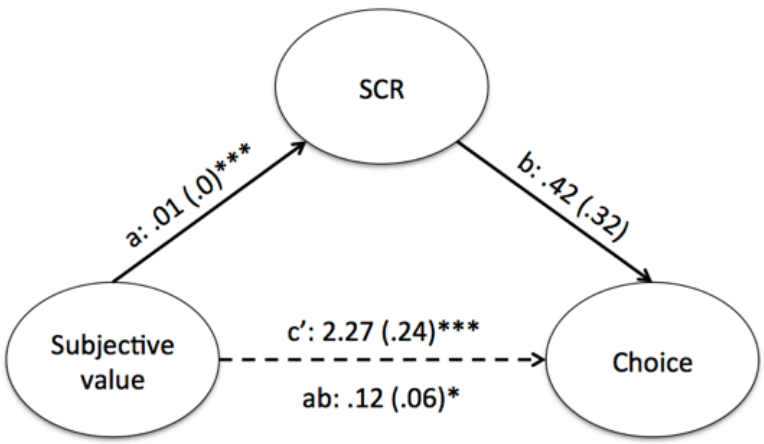

FIG S4 | *Mediation analysis for Ambiguous trials: Subjective Value shows a positive path a effect, indicating higher subjective value increases SCR. Path b effect shows the relationship between SCR and choice. The dashed line represents the direct effect of subjective value on choice (path c'). The suppression effect is below (ab). The mean standardized path coefficients are shown with standard error (in parentheses). *p<0.05, ***p<0.001*

Arousal and Cognitive Load. An alternative explanation of the observed findings is that arousal may be indexing other psychologically meaningful aspects of the decision space, such as cognitive load. To test this, we explored reaction times, since they are known to be a reliable indicator of cognitive demand. Participants took ever so slightly longer to make decisions under ambiguous contexts (mean RT 2.74 SD .12) compared to risky contexts (mean RT 2.73 SD .11, Fig S5; because of the skewed distribution, all reaction times were logged before analysis). We tested the predictive effect of reaction times in the key regression where we find SCR predicts choice (Table 2). This was done to probe whether reaction times accounts for any additional predictive value on choice. We found reaction times did not predict choice: neither a main effect of reaction time nor an interaction or RT and uncertainty type predicted decisions to gamble (Table S9). These results provide further evidence that the relationship between enhanced arousal and increased gambling is not simply a feature of ambiguous choices being more cognitively demanding.

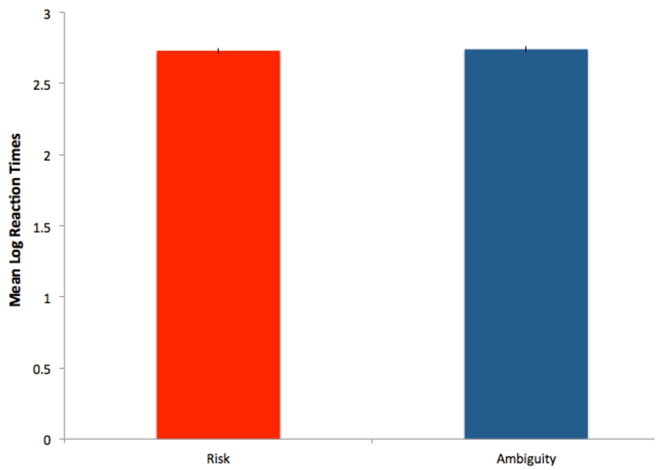

Fig S5 | Reaction time data during risky and ambiguous trials.

TABLE S9: $Choice_{i,t} = \beta_0 + \beta_1 SCR_{i,t} \times \beta_2 Uncertainty\ type_{i,t} + \beta_3 RT_{i,t} \times \beta_4 Uncertainty\ type_{i,t}$

Choice ~ SCR × Uncertainty Type + RT×Uncertainty type; where SCR, RT, and Uncertainty type are all indexed by subject and trial

	Coefficient (β)	Estimate (SE)	z-value	P value
Choice	Intercept	*-0.62 (1.0)*	*-.62*	*0.53*
	SCR	*0.26 (.15)*	*1.68*	*.09*
	Uncertainty Type	*1.04 (1.3)*	*.79*	*.42*
	RT	*0.13 (35)*	*.37*	*.70*
	SCR ×Uncertainty Type	*-0.46 (.16)*	*-.28*	*.004***
	RT×Uncertainty Type	*-0.27 (.48)*	*-.58*	*0.56*

SUPPLEMENTAL DISCUSSION

To date, an explicit link between risk and arousal has proven elusive. While past research illustrates that arousal correlates with discrete aspects of the decision-making space—such as loss aversion—there has been no evidence that arousal correlates with risk sensitivity (Sokol-Hessner et al., 2009). At first glance, that previous research did not observe a relationship between arousal and risk sensitivity may seem surprising considering our current results. However, in this previous study, subjects were presented with lotteries that had known 50% probabilistic win rates (Sokol-Hessner et al., 2009), and in the work here, we too fail to find a relationship with arousal and 50% risk. In fact, our results indicate that the role of arousal in risky contexts appears to be narrowly focused: only when the outcomes are highly risky does arousal increase, signaling that the gamble should not be taken.

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