Supplementary Materials

For

Decision Making Under Uncertainty in Obsessive-Compulsive Disorder

- **S.1 Questionnaires, completed by all participants in the study**.
	- 1. Your age___________
	- 2. Your gender
		- Male
		- \Box Female
	- 3. Your highest level of education
		- 1. Eighth grade or less
		- 2. Some high school
		- 3. Some college or post-high school
		- 4. College Graduate
		- 5. Advanced graduate or professional degree
	- 4. Estimated household income before taxes from all paid employment in the last 12 months
		- 1. \$14,999 or less
		- 2. \$15,000 24,999
		- 3. \$25,000 34,999
		- 4. \$35,000 49,999
		- 5. \$50,000 74,999
		- 6. \$75,000 99,999
		- 7. \$100,000 149,999
		- 8. \$150,000 249,999
		- 9. \$250,000 349,999
		- 10.\$350,000 or more

S.2 The Risk and Ambiguity Task

S.2.1 Detailed task description.

In each trial, participants were presented with a computer representation (**Figure 1**) of a choice between \$5 with certainty and a lottery of a varying winning probability or ambiguity level and a varying \$ amount. Participants had to indicate which option they would prefer by pressing a button. The lottery appeared on the screen in the form of a "bag" painted partly red and partly blue (**Figure 1**). Participants were told beforehand that all the bag s that they would see during the experiment contain a total number of 100 poker chips but that the relative numbers of red and blue chips would be different in different bag s. The proportions of red and blue chips were indicated by the red and blue regions of the bag, and by the number printed inside these regions. Numbers next to the red and blue areas represented the amounts of money that could be made if a chip of that color were drawn from the physical bag to which the display corresponded. For example, in **Figure 1A**, if the participant draws a blue chip, she will win \$50, whereas she will win nothing if a red chip is drawn. Both the left-right position of the lottery and the association of the nonzero outcome with blue or red chips were counterbalanced across trials. On each trial, participants had up to 10 seconds to make a choice; if they did not make a choice by this time the program proceeded to the next trial.

In risk trials, the entire bag was visible, such that participants had complete information about the ratio of red and blue chips in the bag (risky bags; Figure 1A). Five winning probabilities were used, (0.13, 0.25, 0.38, 0.5, and 0.75). In ambiguity trials, part of the bag was hidden by a gray occluder, which was always placed over the center of the

image (Figure 1B). The probability of drawing a chip of a certain color was therefore imprecisely known or ambiguous (ambiguous trials). For example, in Figure 1B, 50% of the chips are occluded, and thus the probability of drawing a red chip can be anywhere between 25% (if all the chips behind the occluder are blue) and 75% (if all the chips behind the occluder are red). Similarly, the probability of drawing a blue chip can also be anywhere between these two values. Figure 1C depicts three ambiguous stimuli used in the experiment. Increasing the occluder size increases the ambiguity level or the range of possible probabilities for drawing a red or blue chip. Three different occluder sizes (covering 24, 50, or 74% of the bag) represent three levels of ambiguity.

Participants were told that each image on the screen represented a physical bag containing physical poker chips in it. Each unique image corresponded to one unique physical bag. For instance, *each and every time they encountered a 25% ambiguous display, they were instructed to think about the same physical bag.* The three ambiguous bags were sealed and were presented to the participants before the beginning of the experiment to ensure that the participants were convinced that the number of red and blue chips could not be adjusted by the experimenters after the participants had made their choices.

Five payoff amounts (5, 8, 20, 50, and 125 dollars) were used at each risk and ambiguity level, yielding 25 unique risk trials and 12 unique ambiguity trials under gains, and 25 unique risk trials and 12 unique ambiguity trials under losses. Each gamble was presented to participants 4 times.

Choices under gains (**G**, 4 blocks) were separated from choices under losses (**L**, 4 blocks). We used two block orders: **GLGLGLGL** and **LGLGLGLG**. We did not find any differences in performance between the two orders. Each block included 40 unique choices (25 choices under risk and 15 choices under ambiguity) in a pseudorandom order, unique for each block.

As participants had been informed at the beginning of the experiment, at the end of the experiment, one trial from the experiment was randomly selected and played for real money. To select the trial, the participant first tossed a die to select one of the eight blocks in the session and then drew a numbered chip from an opaque bag containing 40 chips. The number on the chip indicated which trial in that block would be played for real money. If the participant chose the sure \$5 on that trial, they would receive it; if she chose the lottery, she would draw a chip from the bag corresponding to the lottery of that particular trial and were paid according to the chip's color and the payment contingency on that trial. To make sure that participants don't actually loose the money, in the beginning of the experiment they were endowed with \$125 (the maximal loss in Loss blocks). Those realized earnings (positive or negative) were added to the initial endowment and \$10 show-up fee. Participants were informed of all of these procedures before the experiment began. Providing participants with real monetary rewards was important to make the design incentive compatible, and to avoid a potential hypothetical bias (Loomis, 2011).

S.2.2. A list of all lotteries.

Note: Ambiguity-averse behavior is consistent with the behavior of a decision maker who is pessimistic about imprecise probabilities (assumes that "the odds of winning are against" him or her); ambiguity-seeking behavior is consistent with the behavior of a decision maker who is optimistic about imprecise probabilities (assumes that "the odds of winning favor" him or her).

S.2.3. A quiz that participants had to successfully complete after receiving instructions and before starting the experiment.

1. How many blue chips are there in the bag represented by this lottery?

Type the answer and press "Enter".

(Correct answer: 75)

2. Suppose you played this lottery.

How much would you earn from it if you drew a blue chip?

(Correct answer: \$20)

3. Suppose, you played this lottery and drew a blue chip.

What happens? Press the letter that corresponds to the correct answer (A, B, C or D).

- A. I get \$20
- B. I lose \$20 **(Correct answer)**
- C. I get \$0
- D. I lose \$75
- *4.* How many blue chips are there in the bag that this lottery represents? Press the letter that corresponds to the correct answer (A, B, C, D or E).
	- A. 0
	- B. 100
	- C. exactly 25
	- D. between 25 and 75 **(Correct answer)**
	- E. exactly 75

5. Suppose this trial was randomly selected for payment A: and you chose the option on the RIGHT. How much would you earn?

6. From which lottery are you more likely to draw a blue chip?

(Answer by typing A or B.)

(Correct answer: B)

(Correct answer: \$5)

7. From which lottery are you more likely to draw a red chip? (Answer by typing A or B) A: \$0

(Correct answer: B)

S.3 Behavioral measures

S.3.1. Descriptive measures of choice behavior. We calculated four measures that describe behavior in the decision task: two measures that illustrate value-based decision formation of uncertain options (or attitudes toward uncertainty) and two measures of compliance with subjective value maximization.

Attitudes toward uncertainty. We characterized valuation of uncertain options by measuring risk and ambiguity attitudes. We compared participant's choices in trials containing risky and ambiguous lotteries to the choices of a theoretical decision maker, who is not affected by risk or ambiguity, following Tymula and colleagues (Tymula et al., 2012; Tymula et al., 2013).

Under risk, a risk-neutral decision maker would choose the option of the higher expected value, defined as the probability of a gain multiplied by the magnitude of that gain. In our task, such a decision-maker should choose risky lotteries over the sure payoff 72.5% of the time during Gain blocks, and 27.5% of the time during Loss blocks (SM **S.7**). Participants who chose risky lotteries less (or more) are termed 'risk-averse' (or 'riskseeking'). \$5 lotteries were excluded from these calculations.

Gain blocks:
$$
risk \text{ aversion} = 0.725 - \frac{\text{# of risky lotteries chosen}}{\text{total # of risky lotteries}}.
$$
 (S.1)

Loss blocks:
$$
risk aversion = 0.275 - \frac{\text{# of risky lotteries chosen}}{\text{total # of risky lotteries}}.
$$
 (S.2)

This measure will be positive for a risk-averse decision-maker, and negative for a riskseeking decision-maker.

Under ambiguity, an ambiguity-neutral decision maker would make the same choices regardless of the ambiguity level. Since the range of possible outcome probabilities was centered at 0.5 in all of the ambiguous trials, such a decision-maker should make the same choices in ambiguous trials and in risky (non-ambiguous) trials in which the outcome probability was 0.5. To estimate ambiguity attitudes we therefore compared each participant's choices of ambiguous lotteries to her choices of risky lotteries with 0.5 outcome probability; \$5 lotteries were excluded from these calculations. Participants who chose ambiguous lotteries less (or more) often than they chose 0.5 risky lotteries with the same potential reward are termed 'ambiguity-averse' (or 'ambiguity-seeking').

ambiguity aversion =
$$
\frac{\text{# of 50\% risky lotteries chosen}}{\text{total # of 50\% risky lotteries}} - \frac{\text{# of ambiguous lotteries chosen}}{\text{total # of ambiguous lotteries}}.
$$
 (S.3)

This measure will be positive for decision-makers who are ambiguity-averse and negative for decision-makers who are ambiguity-seeking.

Compliance with the subjective value maximization assumption. The first measure reflects how often participants chose to play a lottery with an uncertain \$5 payoff instead of choosing to receive \$5 with certainty, or how often participants chose -\$5 with certainty instead of playing a lottery with an uncertain -\$5 payoff (i.e. clearly suboptimal choices).

Gain blocks: measure of compliance
$$
1 = \frac{\text{# of uncertain $5 lotteries chosen}{total # of $5 lotteries}
$$
 (S.4)

Loss blocks: measure of compliance
$$
1 = \frac{\text{# of uncertain} - (-\$5) lotteries NOT chosen}{total # of (-\$5) lotteries}
$$
 (S.5)

Subjective value maximization will always favor \$5 with certainty over a \$5 with uncertainty and -\$5 with uncertainty over -\$5 with certainty; thus, an individual wholly guided by the maximization of subjective value should never choose the uncertain option in these trials and should have a score of zero on this measure.

The second measure reflects how often participants behaved inconsistently over the course of the experiment. If on all 4 repetitions of the same pair of options the participant chose the same option (either the lottery or the sure payoff), the choice is classified as consistent; if on some of the 4 repetitions the participant chose the lottery and on other repetitions she chose the sure payoff, the choice is classified as inconsistent. We then calculate the proportion of the total number of unique pairs of options (under both risk and ambiguity) under which the choice was inconsistent. \$5 lotteries were excluded from this calculation, making it independent of the first measure.

$$
measure of compliance 2 = \frac{\# of inconsistent choices}{total * of choices}
$$
 (S.6)

The presence of some inconsistent choices does not necessarily contradict subjectivevalue maximization. However, an increased frequency of such choices in a particular group suggests that value-based decision formation in this group is less sensitive to the differences among the available options.

S.3.2. Inconsistency in choices across identical trials can occur either as a result of violations of subjective-value maximization, or if the subjective values of the options are difficult to distinguish (i.e. when sensetivity to rewards is reduced).

S.3.a.Value based decision making

S.3.b. Noisy valuation

Even though objectively x2 is greater than x1, because of noisy valuation, subjectively x2 is not necessarily greater than x1.

S.3.c. Flat value function

Even though option x1 and x2 appear to be very different, because of the flat value function, subjectively they are indistinguishable.

S.3.3. Model based behavioral measure of fidelity of value-based choice

Each participant's choice data were fit to the most prominent theoretical models of decision making under uncertainty.

Gilboa and Schmeidler (1989):

$$
SV = \begin{cases} \left[p - \beta_{gains} \left(\frac{A}{2} \right) \right] * V^{\alpha_{gains}} \\ - \left[p - \beta_{losses} \left(\frac{A}{2} \right) \right] * (-V)^{\alpha_{losses}} \end{cases}
$$
 (S.7)

where SV is the subjective value, p is the objective outcome probability, A is the ambiguity level around that probability, V is the outcome amount, and α and β are participant-specific parameters for risk and ambiguity attitudes, respectively, with β effectively capturing the relative values a given participant places behaviorally on ambiguous versus risky lotteries.

In Gain blocks ($V \ge 0$), a participant who is risk-neutral will have an α of 1; α < 1 indicates a concave utility function and thus risk aversion; α > 1 indicates convexity and thus risk seeking. In loss trials (V < 0), α < 1(α > 1) indicates risk seeking (aversion). For a participant who is unaffected by ambiguity, β will be 0, and the model will be reduced to a power utility function of a lottery whose winning probability is 0.5 in all of the ambiguous lotteries we examined. An ambiguity-seeking participant would overestimate the likelihood of winning in the gain trials ($β < 0$) and underestimate the probability of losing in loss trials (β > 0). Ambiguity-averse subjects would behave as if they thought that the winning probability was less than 0.5 (β > 0) in gain trials and that the probability of losing was larger than 0.5 (β < 0) in loss trials.

Fitting the choice data with the theoretical model:

Using maximum likelihood estimation, the choice data of each participant was fit with a single logistic function of the form

$$
P_v = \frac{1}{1 + e^{\gamma(SV_F - SV_V)}}\,,\tag{S.8}
$$

where P_v is the probability that the participant chose the variable lottery, SV_F and SV_V are the SVs of the fixed and variable options, respectively, and γ is the slope of the logistic function, or equivalently a noise parameter.

We calculated the goodness of fit, measured by $R²$, for each individual participant for Gain blocks and Loss blocks separately.

S.4 Clinical characteristics of the previous (Pushkarskaya et al., 2015) and the new OCD samples.

Note: Significance of the between-group difference, p-value, for Age, IQ, Income, Education, and clinical scales is based on the one-way ANOVA; significance of the between -group difference, p-value, for Male is based on the Pearson's chi-squared test (χ2). Ham-D17 - Hamilton Depression–17 scale (Hamilton, 1960); Ham-A - Hamilton Anxiety scale (Hamilton, 1959); SI-R - Saving Inventory – Revised (Frost et al., 2004).

S.5 Effect of diagnosis (OCD and/or HD vs. Controls) on frequency of missing responses under risk and ambiguity and during Gain and Loss blocks separately.

Sixteen Controls, 9 individuals with OCD, 4 individuals with comorbid OCD and HD, and 6 individuals with HD missed at least 1 response but never more than 4 responses in each condition (see table S.5.1. below). However, each unique choice was offered 4 times during the experiment, and none of these participants missed the same choice more than once. This means that each participant made each unique choice at least 3 times. All behavioral measures were based on choices that were not missed, and thus were not affected by missed responses.

Distribution of missed responses did not differ between clinical groups and age-matched controls (see table S.5.2 below for Mann-Whitney U test p-value).

Participants	Group	Risk Gains		Risk Losses Ambiguity Gains	Ambiguity Losses
20002	Controls		0	0	0
s10002	Controls			0	O
s10012	Controls	O		0	0
s10014	Controls	O		Ω	3
s10016	Controls	O	O	O	
s10029	Controls				
s10032	Controls	0		O	
s10042	Controls	O			Ω
s10047	Controls				
s10052	Controls	O	O	O	
s10066	Controls	O	∩	O	
s10072	Controls				
s10075	Controls	O	2	ი	
s10077	Controls	O		0	
s20044	Controls				

Table S.5.1. Missed responses for individual participants by experimental condition

Table S.5.2. Independent samples Mann-Whitney U test, p-value

S.6 Effect of diagnosis (OCD and/or HD vs. Controls) on frequency of suboptimal choices

during Gain and Loss blocks separately. Bars: histograms of respective distributions.

S.6.A. 2x2 ANOVA with between subjects factors OCD and HD symptoms

S.7 Limitations of the calibration of the loss trials

While interpreting results from Loss Blocks it is important to remember the following limitation of our study design. The calibration of the loss trials in the existing version of the task allowed only for limited variability in risk and ambiguity aversion under losses. This is illustrated below.

Table S.7.1.a. Probability of choosing a lottery for a hypothetical uncertainty-neutral decision maker under gains.

	\$5	\$8	\$20	\$50	\$125
0.13	$\overline{0}$	0	O	1	1
0.25	$\overline{0}$	0	0.5	1	1
0.38	$\overline{0}$	0	1	1	1
0.5	$\overline{0}$	0	1	1	1
0.75	$\overline{0}$	1	1	1	

Note: Across all choices (excluding \$5 lotteries), an uncertainty neutral participant would chose to gamble 72.5% of the time. Consequently, a risk-averse participant may choose to gamble between 0% and 72.5% of the time. This calibration under gains allows for ample variability in risk aversion across participants.

Table S.7.1.b. Probability of choosing a lottery for a hypothetical uncertainty neutral decision maker under losses.

Note: Across all choices (excluding \$5 lotteries), an uncertainty neutral participant would chose to gamble 27.5% of the time. Consequently, a risk-averse participant may choose to gamble between 0% and 27.5% of the time. This calibration under losses allows limited variability in risk aversion across participants and thus limits power to detect enhanced risk aversion under losses in a clinical population.

Table S.7.2.a. Probability of choosing a lottery for a hypothetical risk- and ambiguityneutral decision maker under gains.

	\$5	\$8	\$20	\$50	\$125
0.25	0				
0.5	0	O			
0.75		0			

Note: Across all choices (excluding \$5 lotteries), an uncertainty-neutral participant would chose to gamble 75% of the time. Consequently, a risk-averse participant may choose to gamble

between 0% and 75% of the time. This calibration allows for a sufficient variability in ambiguity aversion under gains across participants to be sensitive to increased ambiguity aversion in the OCD group.

Table S.7.2.b. Probability of choosing a lottery for a hypothetical risk- and ambiguityneutral decision maker under losses.

Note: Across all choices (excluding \$5 lotteries), an uncertainty neutral participant would chose to gamble 25% of the time. Consequently, an uncertainty-averse participant may choose to gamble between 0% and 25% of the time. This calibration under losses does not allow sufficient variability in ambiguity aversion across participants and thus limits power to detect enhanced ambiguity aversion under losses in the OCD group.

S.8 Uncertainty intolerance during gain and loss blocks, by clinical groups

Note: Significant effects of diagnosis at $p = 0.05$ level are in bold.

S.9 The (lack of) effect of depression and anxiety on decision-making patterns.

Because one potential explanation of uncertainty avoidance is an irrational believe that "the odds are always against me", we anticipated that the severity of depression and anxiety symptoms might affect decision-making patterns in our task. Depression symptoms of all patients were assessed via the Hamilton Depression Rating Scale, Ham-D17 (Hamilton, 1960). Anxiety symptoms of all patients were assessed via the Hamilton Anxiety Rating Scale, Ham-A (Hamilton, 1959). Neither depression symptom severity nor anxiety symptom severity were normally distributed in our sample (Shapiro-Wilk test, p < 0.02). Neither severity of depression nor severity of anxiety correlated significantly with 4 behavioral measures of interest. Proportions of suboptimal choices during gain and loss blocks were not included in this analysis because their distribution extremely deviated from normal.

References:

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