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Decision-making under uncertainty in obsessive–compulsive disorder

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ABSTRACT

Obsessive compulsive disorder (OCD) produces profound morbidity. Difficulties with decision-making and intolerance of uncertainty are prominent clinical features in many patients. The nature and etiology of these deficits are poorly understood. We used a well-validated choice task, grounded in behavioral economic theory, to investigate differences in valuation and value-based choice during decision making under uncertainty in 20 unmedicated participants with OCD and 20 matched healthy controls. Participants' choices were used to assess individual decision-making characteristics. OCD participants did not differ from healthy controls in how they valued uncertain options when outcome probabilities were known (*risk*) but were more likely than healthy controls to avoid uncertain options when these probabilities were imprecisely specified (*ambiguity*). Compared to healthy controls, individuals with OCD were less consistent in their choices and less able to identify options that should be clearly preferable. These abnormalities correlated with symptom severity. These results suggest that value-based choices during decision-making are abnormal in OCD. Individuals with OCD show elevated intolerance of uncertainty, but only when outcome probabilities are themselves uncertain. Future research focused on the neural valuation network, which is implicated in value-based computations, may provide new neurocognitive insights into the pathophysiology of OCD. Deficits in decision-making processes may represent a target for therapeutic intervention.

1. Introduction

Individuals with obsessive–compulsive disorder (OCD) often exhibit indecisiveness, pathological doubt, and avoidance of uncertainty (Rasmussen and Eisen, 1992; Reed, 1985; Tolin et al., 2003), even when the task at hand is unrelated to their primary symptomatology (Hamilton, 1957). OCD was once called 'la folie du doute' ('*the madness of doubt*'), highlighting the central role of self-doubt in its symptomatology (Janet, 1908). The nature and etiology of these deficits are poorly understood.

Decision-making studies, across psychology, economics, and neurobiology, generally assume that individuals aim to maximize some subjective measure of expected value (Rangel et al., 2008). They also recognize that several interrelated but independent processes, including valuation, attention and action selection, are involved in making a value-based choice. Recent neurobiological research has linked one of these processes, computation of subjective value (*valuation*), to activation in the 'valuation network', or 'reward network', which includes the ventral striatum and the ventromedial prefrontal cortex (Bartra et al., 2013). It is an open question whether and to what degree individuals suffering from mental illness comply with this assumption.

Within this framework, indecisiveness and self-doubt may be attributed to impairments in one or several value-based decision formation processes. Consider impaired valuation: when alternatives have distinct subjective values, choice is straightforward (Supplementary Materials; SM S.1, Fig. S.1.a); choices may become difficult, however, if the subjective values of the options are

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imprecisely specified (noisy valuation, Fig. S1.b), or if the options are of similar subjective value (a flat value function, Fig. S1.c). Of note, the circuitry that is linked to valuation (Bartra et al., 2013) is abnormal in OCD (Maia et al., 2008; Menzies et al., 2008). This raises the possibility that abnormalities in valuation may contribute to decision-making difficulties observed clinically in patients.

Impairments in value-based decision formation may cut across traditional diagnostic boundaries (Insel et al., 2010; Dichter et al., 2012), which calls for measures that can detect both an overall impairment in value-based decision formation and particular abnormalities in distinct disease states. With this in mind, we investigated the behavior of individuals with OCD in a decision-making task that allows characterization of different aspects of the process.

We employed the Risk and Ambiguity task (Levy et al., 2010), which has been previously validated in healthy individuals (Tymula et al., 2012, 2013). The task, which consists of choices involving uncertain monetary gains or losses, has several important features. First, it clearly specifies the decision problem on each trial, and provides no feedback about outcomes. This contrasts with more complex tasks, such as the Iowa Gambling Task (IGT; (Bechara et al., 1994)) that additionally require participants to construct a representation of the decision problem based on limited information and that provide feedback, which allows learning. Performance on our task therefore reflects valuation and value-based choice processes (e.g. attention and action selection), independent of learning ability.

Second, the task allows estimating the degree to which participants' choices are consistent with the assumptions of subjective-value maximization. Value-guided decision-makers are expected to adhere to a few simple and intuitive principles, such as choosing one option over another if it is clearly more valuable and to be largely consistent in their choices, unless the available alternatives are close in their subjective values (Fig. S1.b, S1.c). Our task directly examines those issues, independent of participants' individual attitudes towards uncertainty.

Third, the task distinguishes between two forms of uncertainty, which have proven to be dissociable in previous studies (Levy et al., 2010; Tymula et al., 2012, 2013; Camerer and Weber, 1992). A *risky decision* is one in which the outcome is uncertain, but the probabilities of the various possible outcomes are known. An *ambiguous decision* is one in which the outcome probabilities are themselves uncertain. Previous research has shown that individual risk attitudes are largely independent of individual ambiguity attitudes (Camerer and Weber, 1992; Huettel et al., 2006; Cohen et al., 1987; Tymula et al., 2012), stressing the significance of examining both in clinical populations. Tasks that probe decision-making under uncertainty without making this distinction, such as the IGT, may obscure abnormalities that are restricted to one type of uncertainty.

Thus, the task allows evaluating risk and ambiguity attitudes in OCD and, independently, impairments in value-based decision formation processes (valuation and value-based choice). We hypothesized that OCD patients would have elevated uncertainty intolerance, relative to healthy controls, and impaired value-based decision formation, and that these abnormalities would correlate with symptom severity.

2. Methods

2.1. Study design

2.1.1. Participants

All procedures were approved by the Yale University Human Investigation Committee and the Hartford Hospital Institutional Review Board. All participants provided written informed consent and completed a demographic questionnaire, a numeracy scale (SM, S.2), and the Kaufman Brief Intelligence Test (Kaufman, 1979).

Twenty-one OCD patients, unmedicated for at least 8 weeks, were recruited through the Yale OCD Research Clinic and the Anxiety Disorders Center at the Institute of Living, Harford Hospital (SM, S.3). One patient was excluded after failing a drug test. Diagnoses were established by doctoral-level clinicians and confirmed using the Structural Clinical Interview for DSM-IV Disorders (SCID-IV (First et al., 2012)). OCD was the primary clinical diagnosis in all twenty patients; comorbidities included depression (10), hoarding (10), panic disorder (4), and social phobia (1). Within 1 week of behavioral testing we assessed severity of obsessions and compulsions using Yale–Brown Obsessive Compulsive Scale (Y–BOCS (Goodman et al., 1989b, 1989a)) and severity of depression using Hamilton Depression–17 scale (HAM-D17 (Hamilton, 1960)). Fifteen out of 20 OCD patients also completed a Dimensional Yale–Brown Obsessive Compulsive Scale (DY–BOCS), which provides continuous measures of different OCD symptom dimensions (Rosario-Campos et al., 2006).

Twenty participants from the general population (Controls), matched on demographic and cognitive characteristics with the OCD patients (SM, S.4), were recruited in the New Haven, CT area using flyers. Controls did not self-identify as having a psychiatric illness but were not formally assessed using clinical measures and therefore represent the general population, not an artificial diagnosis-free healthy control group. Comparison of the choice patterns of OCD patients with individuals from the general population is more conservative than comparison with diagnosis-free healthy controls.

2.1.2. Risk and ambiguity task

The task (Levy et al., 2010) was developed to study value-based choice and uncertainty attitudes, and is described in detail in SM, S.5. Briefly, participants made 320 sequential choices between a certain and an uncertain payoff; payoffs on 160 of them (grouped in 4 Gain blocks) were positive and payoffs 160 of them (grouped in 4 Loss blocks) were negative (SM, S.6). Here we report data from the Gain blocks (SM, S.7). Participants did not receive any feedback on the outcome of their choices. Each trial entailed a choice between a certain payoff of $5 and a gamble that offered some chance of a positive outcome (between $5 and $125) and some chance of a zero outcome. On risky trials, the lottery payoff and outcome probability were known (Fig. 1A). On ambiguous trials, the payoff was known, but the outcome probability was imprecisely specified (Fig. 1B & C).

On some trials the choice was between a certain and an uncertain payoff of $5. Under these circumstances the certain $5 payoff is clearly more valuable, and so individuals whose decisions are guided by subjective value maximization should always choose the certain $5 payoff. These trials thus allowed estimating the compliance of each participant's choices with subjective expected value maximization.

Each pair of options was offered 4 times. Individuals who are subjective-value maximizers should choose the same option on each repetition, unless the subjective expected values of the two options are difficult to distinguish (SM S1.b, S1.c). Thus, including 4 repetitions of the same pair of options provides another test of compliance with subjective expected value maximization.

Before the experiment, participants were informed that at the end, one trial would be randomly selected and their decision on that trial would result in real monetary consequences. If they picked the certain payoff they would receive $5 (above a $10 fixed payment). If they picked a gamble they would reach into a bag filled with red and blue poker chips in the appropriate proportions; if they drew the winning color they would win between $5 and $125, depending on the gamble.

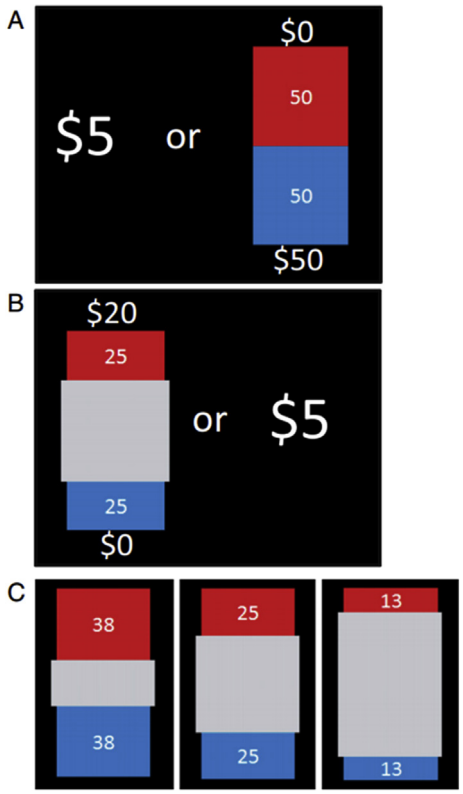

Fig. 1. Experimental design. On each trial, participants chose between $5 and a lottery that varied in both the amount and either the winning probability or the level of ambiguity. The lottery appeared on the screen as a bag containing a total of 100 red and blue poker chips. The red and blue areas of the bag represented the relative numbers of red and blue chips. The numbers next to these areas represented the sums of money that could be won if a chip of that color were drawn ($5, $8, $20, $50, or $125, depending on the trial; SM, S.6). A: In risky trials, the lottery payoff and outcome probability were precisely specified. The number of chips associated with a winning color was 13, 25, 38, 50, or 75, depending on the trial (SM, S.6). B: In ambiguous trials, part of the bag was hidden by a gray occluder. Thus the number of chips associated with a winning color was uncertain, C: 3 levels of uncertainty were used. The number of chips associated with a winning color belonged to a small (between 38 and 62), medium (between 25 and 75), or wide (between 13 and 87) range, always centered around 0.5 probability (SM, S.6).

All participants were quizzed on how well they understood the task and practiced at least once on a short 16- trial version of the experiment, for no payment. Only after they successfully completed the quiz (SM S.8) and felt comfortable with the task did they proceed to the experiment.

2.2. Data analysis

2.2.1. 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.

2.2.1.1. 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, 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 (SM S.7). Participants who chose risky lotteries less (or more) are termed 'risk-averse' (or 'risk-seeking'). $5 lotteries were excluded from these calculations.

$$risk\ aversion = 0.725 - \frac{\#\ of\ risky\ lotteries\ chosen}{total\ \#\ of\ risky\ lotteries}.$$

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

$$ambiguity\ aversion = \frac{\#\ of\ 50\%\ risky\ lotteries\ chosen}{total\ \#\ of\ 50\%\ risky\ lotteries} - \frac{\#\ of\ ambiguous\ lotteries\ chosen}{total\ \#\ of\ ambiguous\ lotteries}.$$

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

2.2.1.2. 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.

$$measure\ of\ compliance\ 1 = \frac{\#\ of\ uncertain\ \$5\ lotteries\ chosen}{total\ \#\ of\ \$5\ lotteries}$$

Subjective value maximization will always favor $5 with certainty over a $5 with uncertainty; 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.

$$measure\ of\ compliance\ 2 = \frac{\#\ of\ \ inconsistent\ choices}{total\ \#\ of\ choices}$$

The presence of some inconsistent choices does not necessarily contradict subjective-value 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.

2.2.2. Model-based analysis of the choice data

As a follow up analysis, we also looked at how well the choice data of each participant fit with a theoretical model of subjective value-guided decision-making. Model-based analysis of the choice data is more comprehensive than the two measures of compliance described above, because it accounts for potential randomness of choices and for non-linearity in subjective value. Therefore, worse model fit in one group compared to another implies that the choices of individuals from that group are less consistent with the assumptions of the model, and that the estimated model parameters are less likely to describe specific characteristics of individuals from that group. It is virtually impossible, however, to test all alternative value-based decision models. We therefore present the model-based analysis only for illustrative purposes.

Numerous models have been proposed to describe the subjective value of risky and ambiguous options in decision-making tasks (Camerer and Weber, 1992). We fit the choice data of each participant with the two most prominent models ((Gilboa and Schmeidler, 1989) and (Hsu et al., 2005); SM S.9), and calculated the goodness of fit, measured by R^2, for each individual participant. The results from the two models were almost identical for both OCD patients and Controls (SM S.10); we present the results from one of the two models (Gilboa and Schmeidler, 1989).

2.2.3. Task correlates with clinical measures

We examined the effect of diagnosis (OCD vs. Controls) on each of the task measures described above. First, we tested the distribution of each of the measures for normality (using the Shapiro–Wilk test). Second, we employed nonparametric (Mann–Whitney U or nonparametric ANCOVA (Akritas et al., 2000)) tests for measures that violated the assumption of normality, and one-way ANOVA and ANCOVA for measures that were distributed normally. In the ANCOVA analyses, the task measures were dependent variables, group (OCD vs. Controls) was the independent variable. IQ and age were included as covariates. Income was not included, because it did not correlate with any of the behavioral measures ($p > 0.23$ for all measures); education and numeracy scores were not included, because they significantly correlated with the IQ score ($p < 0.01$).

Finally, we tested the correlations between the behavioral measures and selected clinical measures. We used Spearman's correlation for measures that were not distributed normally, and Pearson's correlation for measures that were distributed normally. Clinical measures included individual scores on Y–BOCS total, Y–BOCS obsession subscale, Y–BOCS compulsion subscale, DY–BOCS harm subscale, and DY–BOCS symmetry subscale (less than a half of the OCD participants reported any symptoms along the remaining DY–BOCS subscales, and they were therefore not used in the analysis).

Nonparametric ANCOVAs were performed using R 3.1.2; all other statistical analyses were performed using SPSS Statistics 21.

3. Results

3.1. Uncertainty attitudes

'Risk' occurs when the probabilities of uncertain outcomes are clearly specified; risk aversion (Methods) measures the extent to which an individual avoids (or devalues) a risky option, relative to its expected value. Risk aversion was normally distributed in Controls but not in OCD. There were no difference in risk aversion between OCD and Controls ($p = 0.57$, Fig. 2A). This result held when we controlled for age and IQ ($p = 0.37$).

'Ambiguity' describes uncertainty that occurs when the probabilities of the alternative outcomes are themselves uncertain. Ambiguity aversion (Methods) is a choice pattern that indicates avoidance (or devaluation) of options that entail ambiguity, relative to a similar option that entails only risk. Ambiguity aversion was normally distributed in Controls but not in OCD. Individuals with OCD were significantly more ambiguity-averse than Controls ($p = 0.04$, Fig. 2B). This difference remained significant when we controlled for age and IQ ($p = 0.045$). This result is consistent with our hypothesis that OCD are more uncertainty intolerant than Controls.

Next, we examined the relationship of risk and ambiguity aversion to measures of clinical symptoms in OCD. The distribution of ambiguity aversion in OCD appeared bimodal (Fig. 2B), suggesting that ambiguity-averse OCD participants may represent a subgroup. However, no measured clinical or demographic characteristic was clearly associated with elevated ambiguity aversion (SM S.11), although our power to detect such an association was low. Neither risk nor ambiguity scores correlated significantly with total OCD symptom severity (Y–BOCS) or with DY–BOCS measures of different dimensions of OCD symptomatology; this latter analysis was limited by the fact that only 15 of the 20 completed the DY–BOCS scale, and only two of the DY–BOCS measures – harm avoidance and symmetry – were represented with sufficient diversity in our sample to permit meaningful correlation analysis. There was no association between risk or ambiguity aversion and depressive symptoms (SM S.12).

3.2. Fidelity to subjective value maximization in OCD

In choices between a certain and an uncertain $5, the certain payoff is equivalent to the uncertain option in magnitude and clearly superior to it in probability. The number of times a participant chooses the uncertain payoff under these circumstances is thus a measure of violations of subjective-value maximization. These choices were non-normally distributed in both OCD and Controls. Participants with OCD chose the uncertain payoff significantly more often than Controls ($p = 0.04$, Fig. 3A); this difference remained significant when we controlled for age and IQ ($p = 0.02$). The distribution on this measure in the OCD group again appeared bimodal (Fig. 3A), but no clinical or demographic characteristics clearly identified the 'outliers' (SM S.11); only a single participant was an 'outlier' both on this measure and on the ambiguity aversion measure (Fig. 2B).

Inconsistency in choices across identical trials can occur as a result of violations of subjective-value maximization, or if the subjective values of the options are so close to each other that they are difficult to distinguish (SM S.1). Choice consistency was normally distributed in both OCD and Controls. OCD showed significantly greater inconsistency in choices than Controls ($p = 0.037$, Fig. 3B); this difference remained significant when we controlled for age and IQ ($p = 0.03$). The two measures of fidelity to subjective value maximization (Fig. 3A and B) correlated marginally (Spearman's $\rho = 0.306$, $p = 0.055$).

To further explore the observation that subjects with OCD violated the expectations of subjective value-guided decision-making more than Controls, we fitted the choice data of each individual participant with a theoretical model of subjective expected value (Gilboa and Schmeidler, 1989). Fig. 4A depicts the fit of the choice data of a representative OCD patient (top) and a representative control participant (bottom) with the model. We calculated model fit (R^2) for each participant; it was normally distributed across subjects in both OCD and control groups (Shapiro–Wilk $p > 0.1$). Individual R^2 correlated with both the number of $5 lotteries chosen over the certain $5 (Spearman's $\rho = -0.61$, $p < 0.001$)

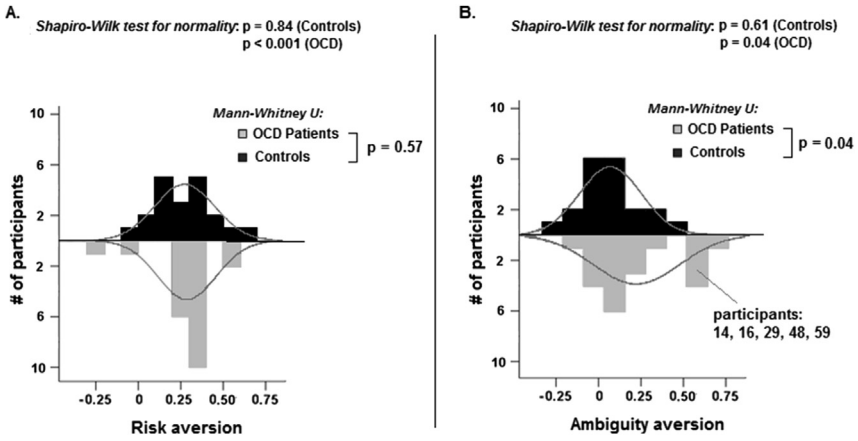

Fig. 2. Risk and ambiguity aversion in OCD participants and controls. We examined the effect of diagnosis (OCD vs. Controls) on risk aversion (A) and ambiguity aversion (B) separately. Bars: histograms of respective distributions. Curves: empirically approximated normal curves. A: Risk aversion distributions in OCD and control participants. A Mann–Whitney U test failed to reject the null hypothesis that OCD and control participants were drawn from the same distribution. B: Ambiguity aversion distributions in OCD and control participants. Individuals with OCD showed higher ambiguity aversion compared to Controls (Mann–Whitney U test). The group of participants with the highest values of ambiguity aversion includes participants 14 (Y–BOCS = 26), 16 (Y–BOCS = 29), 29 (Y–BOCS = 11), 48 (Y–BOCS) = 26, and 59 (Y–BOCS = 34). Symptom severity of 3 out of 5 of these subjects is very close to the sample average (Y–BOCS = 27 ± 8); one scores lower and one scores higher than a group average. Thus the observed difference in the ambiguity attitudes cannot be attributed to the difference in the overall symptom severity. For more details on how individual characteristics of these participants are compared to the sample average see SM, S.11.

and the number of inconsistent choices (Pearson r = −0.79, $p < 0.001$), reinforcing the notion that it is a more comprehensive measure of the fidelity of participants' choice behavior to the subjective expected value maximization assumption (SM S.13). We tested for group differences, and found that the choices of individuals with OCD fit the model significantly worse than the choices made by Controls (Fig. 4B), illustrating the possibly impaired value-based decision formation in OCD**.** Due to the poor model fit in OCD we did not use the model-based parameters in further analysis of risk and ambiguity, as has been done in previous work in healthy participants ((Tymula et al., 2012, 2013); SM S.14).

In an exploratory analysis, we correlated model fit estimates (R^2) with measures of OCD symptom severity within the OCD group. R^2 did not correlate significantly with overall OCD severity (Y–BOCS), but it strongly correlated, negatively, with the severity of harm avoidance in OCD patients (DY–BOCS harm avoidance; see Table 1 & Fig. 4C).

3.3. Comparison to a larger control sample

To test the generality of these results, we compared our OCD sample to a larger group of Controls (N = 40; this larger group of Controls was less well matched to OCD subjects on education and income, which is why this was not the primary analysis). All of the findings summarized above were also seen in comparison to this larger group (SM, S.15).

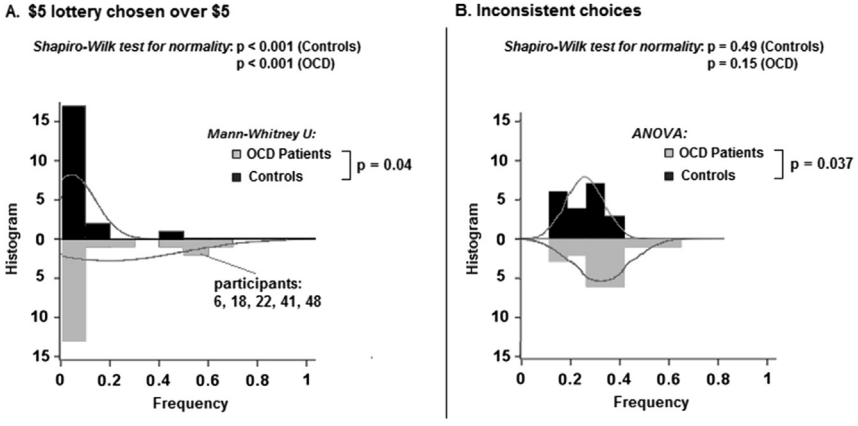

Fig. 3. Fidelity to subjective value maximization in OCD participants and controls. Effect of diagnosis (OCD vs. Controls) on two measures of complience with subjective value maximization. Bars: histograms of respective distributions. Curves: empirically approximated normal curves. A: Frequency of $5 lottery chosen over $5, in OCD and control participants. OCD participants chose these lotteries significantly more often than controls (Mann–Whitney U test). The group of participants with the highest values of ambiguity aversion includes participants 14 (Y–BOCS = 26), 16 (Y–BOCS = 29), 29 (Y–BOCS = 11), 48 (Y–BOCS) = 26, and 59 (Y–BOCS = 34). Symptom severity of 3 out of 5 of these subjects is very close to the sample average (Y–BOCS = 27 ± 8); one scores lower and one scores higher than the group average. Thus the observed difference in the ambiguity attitudes cannot be attributed to the difference in the overall symptom severity. For more details on how individual characteristics of these participants are compared to the sample average see SM, S.11. B: Frequency of inconsistent choices in OCD and control participants. OCD participants were significantly more inconsistent in their choices than control participants (one-way ANOVA).

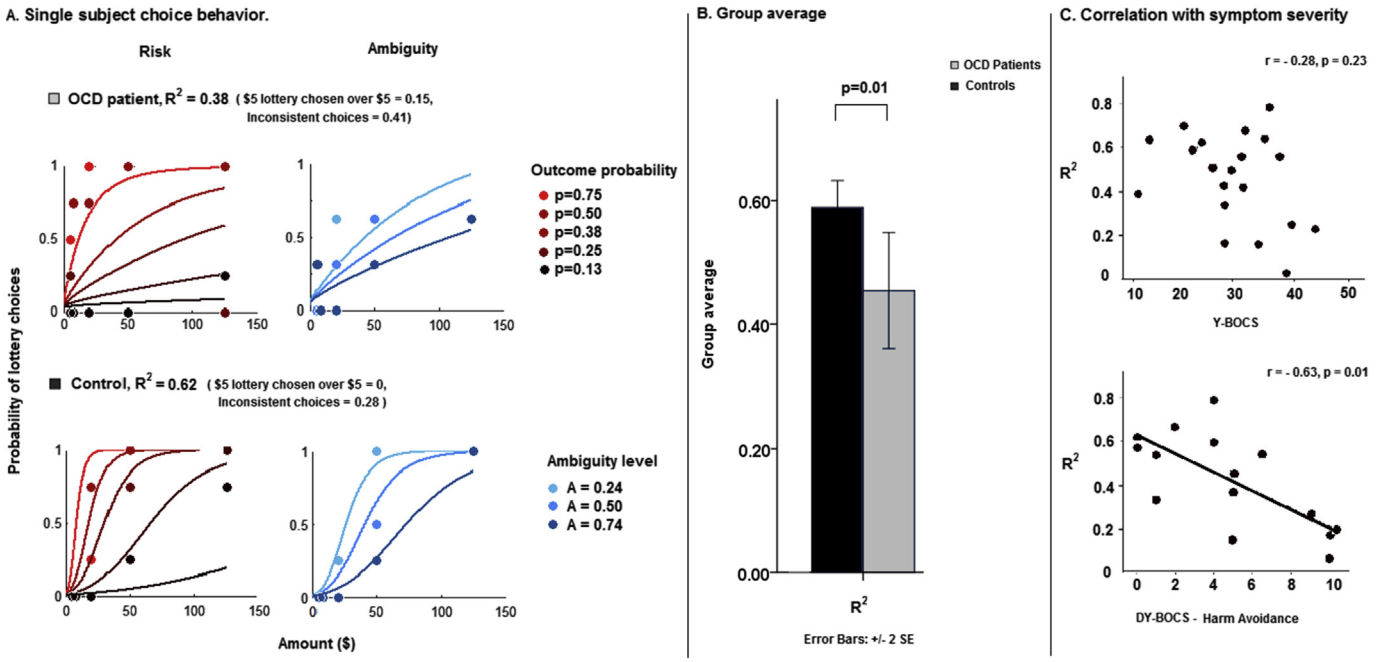

Fig. 4. The goodness of fit of the choice data to the subjective value theoretical model. A: Single subject choice behavior. The graphs present the proportion of trials in which a representative OCD participant (top) and a representative control participant (bottom) chose the lottery over the certain amount ($5), as a function of the offered lottery amount, in risky (left) and ambiguous (right) trials. Different curves are for different risk or ambiguity levels. R^2, goodness of fit. B: Group average. A theoretical model by Gilboa and Schmeidler (1989) fit the data from control participants significantly better than the data from OCD participants. Note that the R^2 of the representative OCD and control participants (A) are within the margin of error of the respective group average. C: Correlations with symptom severity. A measure of goodness of fit (R^2) of choice data to a theoretical model by Gilboa and Schmeidler (1989) is plotted as a function of Y–BOCS total score (top) and severity of harm avoidance (bottom) in OCD patients.

4. Discussion

We examined the behavior of OCD and control participants using a decision task that tests several sub processes of value-based decision formation (valuation and value-based choice) in the presence of uncertainty (Fig. 1). We found that OCD did not differ from Controls in their attitudes towards risk (Fig. 2A) but were more avoidant of ambiguity (Fig. 2B). This is consistent with clinical observations of uncertainty intolerance in OCD patients (Tolin et al., 2003) but indicates that it is critical to distinguish between different types of uncertainty in order to demonstrate this abnormality clearly. We also found that OCD were less compliant with the assumptions of subjective value maximization than Controls (Figs. 3 and 4), suggesting impairments in valuation or value-based choice.

The idea that ambiguity, but not risk, avoidance may be abnormal in OCD has been suggested previously (Starcke et al., 2010; Zhang et al., 2015) and has been proposed as a potential endophenotype for OCD (Zhang et al., 2015). Past studies, however, have used more complicated decision tasks, the IGT (Bechara et al., 1994) and the Game of Dice Task (Brand et al., 2005). While these tasks do require decision-making under uncertainty, their complexities raise interpretive challenges. A major confound in the IGT is that feedback leads to learning about reward probabilities over the course of the task. Therefore, while choices early in the IGT can plausibly be described as being made under ambiguity, it is less clear that this is the case later in the task. Furthermore, abnormal performance on IGT does not clarify what basic process is impaired: valuation and value-based choice, or learning and forming beliefs about the environment (Buelow and Suhr, 2009).

Ambiguity and risk attitudes appear to have distinct neural substrates (Huettel et al., 2006). Follow-up neurobiological studies may particularly focus on networks associated with ambiguity processing in OCD. The distribution of ambiguity aversion scores in

Table 1
Correlations between symptom severity and behavioral measures.

Shapiro–Wilk, p		N	$5 lottery chosen over $5	Inconsistent choices	Model fit, R^2	Risk aversion	Ambiguity aversion
			0.00	0.34	0.63	0.00	0.04
Y–BOCS, total	*r, Pearson*	20	–	0.31	−0.35	–	–
	ρ, Spearman's		0.26	–	–	−0.06	−0.17
Y–BOCS, obsessions	*r, Pearson*	19	–	0.29	−0.35	–	–
	ρ, Spearman's		0.17	–	–	−0.17	−0.11
Y–BOCS, compulsions	*r, Pearson*	19	–	0.22	−0.24	–	–
	ρ, Spearman's		0.20	–	−0.19	−0.07	−0.14
DY–BOCS, harm	*r, Pearson*	15	–	0.38	−0.63*	–	–
	ρ, Spearman's		0.08	–	–	−0.42	0.03
DY–BOCS, symmetry	*r, Pearson*	15	–	0.26	−0.29	–	–
	ρ, Spearman's		0.05	–	–	−0.16	−0.18

Note: *- significance at p = 0.01 level uncorrected, or at p = 0.05 level corrected for multiple comparisons.

our OCD sample appeared to be bimodal (Fig. 2B); follow-up studies in larger and more heterogeneous samples may clarify whether a discrete subset of OCD patients exhibits ambiguity aversion.

The Risk and Ambiguity task has the added benefit of providing three distinct measures of compliance with the assumptions of subjective value maximization. We find the choices of individuals with OCD to be less consistent with subjective value maximization than those of Controls, under both risk and ambiguity. This might indicate more basic impairments in value-based decision formation. To the best of our knowledge, no previous behavioral measure has captured this impairment in OCD. Deficits in this domain, however, are consistent with evidence from other investigations (Figee et al., 2011). For instance, individuals with OCD have abnormal activation patterns in the valuation network, which includes the orbitofrontal cortex, basal ganglia and thalamus (Cavallaro et al., 2003), consistent with the proposition that valuation, a central process of value-based decision formation, might be impaired in OCD. Follow-up studies may test more measures of individual compliance with the value-based decision framework. Such studies may also explore in a more targeted manner possible impairments in distinct value-based decision formation processes (valuation, attention, action selection), as well as in interactions among those processes.

Of note, we did not investigate the motivations behind the choices or the subjective perceptions of uncertainty. Recent studies (Dar, 2004; Stern et al., 2013; Banca et al., 2015) have focused on these questions and found that OCD are less confident in their choices, and more uncertain regarding whether their actions have been performed correctly. Our goal was to derive objective behavior-based measures that may reliably characterize OCD and potentially be used in follow up studies of neurobiological impairments.

A limitation of our study is that it is based on the comparison of two small ($N = 20$) groups. Replication of all results in a comparison with a larger control group (SM S.15) confirmed all effects. However, replication in a larger OCD sample is needed, as are significantly larger samples from the general population to provide a reliable benchmark for comparison with clinical groups.

In exploratory analyses, we found evidence for an association of harm-avoidance symptoms with a deficit in value-based decision formation (Fig. 4C). The harm avoidance dimension encompasses checking symptoms (Rosario-Campos et al., 2006). It is tempting to speculate that a deficit in outcome valuation may lead to uncertainty in evaluating the value of outcomes of decisions and actions and thus to a need to check. However, our findings in this area are limited by the fact that only 15 of our subjects completed the DY–BOCS and by the fact that only two of the symptom dimensions that it measures, harm avoidance and symmetry, were represented with sufficient variance to permit informative correlation analysis. Furthermore, harm-avoidance negatively correlated with an individual measure of model fit, not with a tendency to violate one of the assumptions of the subjective value framework. Future studies need to recruit larger samples in which other OCD dimensions are better represented. Future studies also need to recruit participants with subclinical OCD tendencies, unaffected OCD relatives, and individuals with OCD-related disorders. Such studies will establish whether these decision-making abnormalities constitute an endophenotype and whether they cut across traditional diagnostic categories.

Author contribution

Helen Pushkarskaya – design, data collection and analysis, interpretation of the results, article preparation.

David Tolin – data collection, interpretation of the results, article preparation.

Lital Ruderman – data collection and analysis, interpretation of the results, article preparation.

Ariel Kirshenbaum – data collection, interpretation of the results, article preparation.

J. MacLaren Kelly – data collection, interpretation of the results, article preparation.

Christopher Pittenger – design, data collection and analysis, interpretation of the results, article preparation.

Ifat Levy – design, data collection and analysis, interpretation of the results, article preparation.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jpsychires.2015.08.011.

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