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A model-based analysis of decision making under risk in obsessive-compulsive and hoarding disorders

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ABSTRACT

Attitudes towards risk are highly consequential in clinical disorders thought to be prone to "risky behavior", such as substance dependence, as well as those commonly associated with excessive risk aversion, such as obsessive-compulsive disorder (OCD) and hoarding disorder (HD). Moreover, it has recently been suggested that attitudes towards risk may serve as a behavioral biomarker for OCD. We investigated the risk preferences of participants with OCD and HD using a novel adaptive task and a quantitative model from behavioral economics that decomposes risk preferences into outcome sensitivity and probability sensitivity. Contrary to expectation, compared to healthy controls, participants with OCD and HD exhibited less outcome sensitivity, implying less risk aversion in the standard economic framework. In addition, risk attitudes were strongly correlated with depression, hoarding, and compulsion scores, while compulsion (hoarding) scores were associated with more (less) "rational" risk preferences. These results demonstrate how fundamental attitudes towards risk relate to specific psychopathology and thereby contribute to our understanding of the cognitive manifestations of mental disorders. In addition, our findings indicate that the conclusion made in recent work that decision making under risk is unaltered in OCD is premature.

1. Introduction

It is commonly believed that so-called "risky behavior" is over-represented in mental disorders. Examining attitudes towards risk may be particularly fruitful in disorders hypothesized to be characterized by impulsivity, such as substance use disorders (SUD), as well as in those commonly regarded as excessively risk averse, such as obsessive-compulsive disorder (OCD) and hoarding disorder (HD). Current models of OCD and HD assert that both disorders involve impaired decision making (Cavedini et al., 2002; Grisham et al., 2010; Tolin and Villavicencio, 2011; Woody et al., 2014), and it has been suggested that abnormal attitudes towards uncertainty play a fundamental role in both (Admon et al., 2012; Grisham et al., 2010; Starcke et al., 2010; Zhang et al., 2015). In particular, the most prominent models of OCD and HD implicate excessive risk aversion and intolerance of uncertainty (Pushkarskaya et al., 2015).

The first studies to examine risk preferences in OCD and HD primarily utilized the Iowa Gambling Task (IGT) (Bechara et al., 1994). Studies based on the IGT have yielded mixed results. Lawrence et al. (2006) found evidence of a "link between hoarding and [increased] risky behavior on the IGT," while the OCD group did not differ from controls. In contrast, neither Grisham et al. (2007), nor Tolin and Villavicencio (2011) found that hoarding participants differed from controls on the IGT (Grisham et al., 2007; Tolin and Villavicencio, 2011). A large study by Mackin and colleagues found no differences between HD, OCD, or age matched controls on the IGT (Mackin et al., 2015). The IGT was designed as a measure of impatience and probabilistic learning, and its suitability as an assessment of risk preferences has been questioned in recent years (Buelow and Suhr, 2009; Pushkarskaya et al., 2015). Sohn et al. (2014) utilized the Balloon Analogue Risk Task (BART) and found lower levels of risk taking in OCD relative to HC. Several recent studies have utilized tasks more appropriate for the quantification

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of risk preferences and have found evidence that subjects with OCD differ from HC in decision making under *ambiguity* (decisions between uncertain outcomes with uncertain probabilities), exhibiting greater ambiguity aversion, but do not differ from HC in decision making under *risk* (outcome probabilities are known) (Pushkarskaya et al., 2015; Starcke et al., 2010; Zhang et al., 2015).

Perhaps one reason that previous work has been inconclusive is that decision making under risk is a complex process involving multiple distinct subprocesses (Sokol-Hessner et al., 2015; Tversky and Fox, 1995). The fact that individuals frequently purchase both disaster insurance and lottery tickets indicates that people are not defined by a single risk preference. Significant controversy exists with regard to whether individual risk preferences are domain-specific (e.g., risky choices about stock investments versus alcohol consumption) (Weber et al., 2002; Weber and Johnson, 2009), or stable and domain-general (Einav et al., 2012; Pushkarskaya et al., 2015). Economic analyses have tended to find greater evidence for domain-general risk preferences (Einav et al., 2012), while studies from the psychology literature have been more likely to find that risk preferences are largely domain-specific (Weber et al., 2002; Weber and Johnson, 2009).

In the current study, we take advantage of tools from behavioral economics and recent advances in machine learning that permit a quantitative, dimensional analysis of decision making under risk that extends beyond the group-level summary measures of traditional decision making experiments. Tools from economics may prove especially useful in the characterization of alternative phenotypes, or endophenotypes, of mental disorders because they target specific cognitive processes thought to be impaired (Bickel et al., 2007; Hartley and Phelps, 2012; Sharp et al., 2012). Given the potential of such behavioral endophenotypes for refining the nosology of mental disorders (Insel et al., 2010), it is not surprising that tools from behavioral economics have been gaining popularity in the study of mental illness (Bickel et al., 2011; Hartley and Phelps, 2012; Sharp et al., 2012).

In economics, risk aversion is defined as “a preference for a sure outcome [e.g., $5 guaranteed] over a prospect with equal or greater expected value [e.g., 25% chance of receiving $20 dollars]” (Tversky and Fox, 1995). An individual's preferences over outcomes are summarized with a utility function; linear utility functions imply risk-neutrality, concave utility functions imply risk aversion, and convex functions imply risk seeking. Tversky and Kahneman demonstrated that participants tend not to have a single characteristic risk attitude (i.e., pure risk aversion vs. pure risk-seeking); the most common pattern involves overweighting of small probabilities along with underweighting of high probabilities (Kahneman and Tversky, 1979). This pattern is consistent with the popularity of both lottery tickets (small probability of large reward) and disaster insurance (small probability of large loss), and can account for well-known behavioral findings such as the certainty effect (the overweighting of outcomes that are certain relative to those that are highly probable) (Kahneman and Tversky, 1979).

To account for these complexities, Tversky and Kahneman introduced the “probability weighting function” (PWF), which transforms objective probabilities into subjective probability *weights* (Kahneman and Tversky, 1979). The PWF is a central component of Cumulative Prospect Theory (CPT) (Tversky and Kahneman, 1992), the most popular and empirically successful theory of decision making under risk in behavioral economics. As shown in Fig. 2, the case in which subjective probability weights equal objective probabilities corresponds to a linear PWF, which is classically accepted as the standard of rational choice in economics (Tversky and Wakker, 1995). Empirical findings are better accounted for by *nonlinear* PWFs (Camerer and Ho, 1994; Gonzalez and Wu, 1999).

The CPT model affords a more nuanced description of risk preferences than the standard economic framework. In place of a single measure of risk seeking or aversion, risk preferences are decomposed into “outcome sensitivity” and “probability sensitivity.” The curvature of the value function (the CPT analogue of the classical utility function) captures outcome sensitivity, while the PWF captures probability sensitivity (Glöckner and Pachur, 2012). Generally, a concave value function (i.e., diminishing sensitivity to larger outcomes) is associated with risk aversion.[1] For that reason, we hypothesized that the clinical populations would exhibit greater concavity of the value function than healthy controls, on average.

2. Methods and materials

2.1. Participants

Individuals ≥18 years of age with OCD (n = 29, 17 female; mean age = 35, SD = 13), HD but not OCD (n = 29, 19 female; mean age = 58, SD = 11), and healthy controls (HC; n = 28, 14 women; mean age = 46, SD = 16) participated. The participants were part of a larger study that included a comprehensive clinical assessment, neuropsychological battery, and electrophysiology (EEG) measurements. Psychosis, dementia, intellectual disability, history of head trauma with loss of consciousness, active substance abuse, current use of antipsychotic medications, or any medical conditions known or suspected to affect cognitive function were exclusionary criteria. The majority of participants in the OCD and HD groups suffered from a comorbid depressive disorder (Major Depressive Disorder (MDD), Dysthymic Disorder) and/or an anxiety disorder (Generalized Anxiety Disorder (GAD), panic disorder, specific phobia, social phobia). Participants in these groups were excluded if they met criteria for any other active DSM-IV-TR Axis I disorders in the past year. Diagnosis of OCD, as well as absence of exclusionary psychiatric disorders, was confirmed using the Structured Clinical Interview for DSM-IV (SCID) (First et al., 2002). Subjects with OCD were excluded if they endorsed significant hoarding symptoms. HD diagnosis was determined according to DSM-V criteria (APA, 2013). HC participants were excluded if they met criteria for active DSM-IV-TR Axis I diagnoses within the past year. Sample size target of 30 per group was selected on the basis of previous findings of similar studies in the literature (Grisham et al., 2010; Sokol-Hessner et al., 2009). Participants were recruited from mental health clinics, media advertisements, and the Mental Health Association of San Francisco. Written informed consent was obtained from all participants under protocols approved by the Institutional Review Board of the University of California, San Francisco.

2.2. Clinical measures

For the parent study, participants received extensive clinical assessments. We focused on the results of a relevant subset of these measures: the Saving Inventory, Revised (SI-R) (Frost et al., 2004), the UCLA Hoarding Symptom Scale (UHSS) (Saxena et al., 2007), the Yale Brown Obsessive Compulsive Scale (YBOCS) (Goodman et al., 1989), the Beck Depression Inventory (BDI) (Beck et al., 1961), and the Beck Anxiety Inventory (BAI; Beck et al., 1988).

[1] Technically, due to the influence of the PWF, a concave value function would not be sufficient to guarantee overall “risk aversion” (Schmidt and Zank, 2008). Following previous authors (Neilson and Stowe, 2002), we will attribute risk aversion, neutrality, or seeking to the value function, rather than to the individual participant or group.

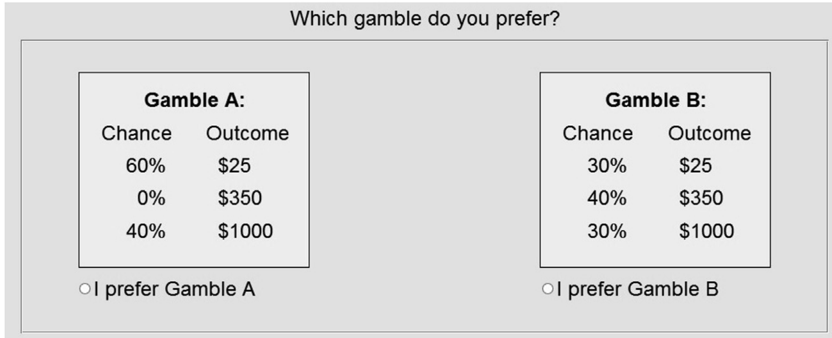

Fig. 1. Example experimental task trial.

2.3. Decision making task

Each participant completed a sequence of 52 trials in which pairs of probabilistic rewards (gambles) were presented. Each gamble was presented as a "game of chance" that could yield a reward of \$25, \$350, or \$1000, with specified probabilities (See Fig. 1). In each trial, participants were required to indicate which gamble they preferred by clicking the appropriate box on a computer screen.

The specific probabilities in each trial of each possible reward were determined in real time for each participant using adaptive design optimization (ADO; see Supplemental Material for details), a machine learning tool designed to improve measurement precision in experimentation. Like adaptive testing in educational testing (e.g., GRE), in which sequences of correct answers result in progressively more difficult questions, the principles formalized in ADO result in more precise estimates of the specific risk attitudes of the participant (Cavagnaro et al., 2009). ADO has been utilized to identify best-fitting parameters in delay discounting (Cavagnaro et al., 2016), probability-weighting in healthy controls (Cavagnaro et al., 2013b), and memory retention (Cavagnaro et al., 2010).

2.4. Model fitting

Participant choice data were modeled at the individual and group levels using the CPT model (Tversky and Kahneman, 1992), which is comprised of two component functions: the value function and the PWF. For a three-outcome gamble $g=(p_1,x_1;p_2,x_2;p_3,x_3)$, where $x_1<x_2<x_3$, CPT assigns a utility using the formula

$$u(g)=w(p_3)v(x_3)+(w(p_2+p_3)-w(p_3))v(x_2)+(w(p_1+p_2+p_3)-w(p_2+p_3))v(x_1),$$

where $w(p_i)$ is the PWF and $v(x_i)$ is a monotonic value function.

Numerous parametric forms have been proposed for the value function, with a one-parameter power function being the most popular. We follow Cavagnaro et al. (2013a) in using a "parameter free" specification, which is more flexible than a power function. Since all gambles in our experimental design have the same three distinct reward values, \$25, \$350, and \$1000, we may assume without loss of generality that $v(\$25)=0$, $v(\$1000)=1$, and $v(\$350)=v$, where $0\le v\le 1$ is a free parameter (Cavagnaro et al., 2013a). Thus, the above equation simplifies to

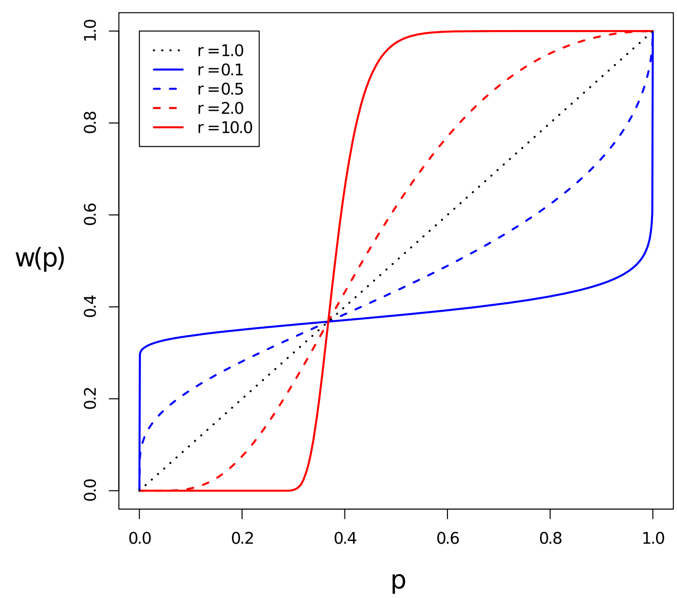

Fig. 2. Plots of the probability weighting function for various values of the r parameter. p: objective probability; $w(p)$: probability weight transformation.

$$u(g)=w(p_3)+(w(p_2+p_3)-w(p_3))\times v.$$

The magnitude of the v parameter determines the contribution of the value function to risk preferences[2]: $v=\frac{1}{3}$ indicates risk neutrality, while $0<v<\frac{1}{3}$ indicates risk seeking, and $\frac{1}{3}<v<1$ indicates risk aversion (Table 1). Following Prelec (1998), PWF parameter estimates were obtained using the formula

$$w(p)=e^{-(-\ln p)^r},$$

where p is the objective probability and $r>0$ is a free parameter (see Supplemental Material for details). Fig. 2 plots the PWF for a few illustrative values of r. When r is less than one, the curve has

Table 1
Dimensions risk preference captured by parameters of the CPT model.

Dimension	Parameter	Interpretation
Risk aversion	v	$v<\frac{1}{3}\rightarrow$ risk seeking
		$v>\frac{1}{3}\rightarrow$ risk averse
Probability weighting	r	$r<1\rightarrow$ inverse s shape
		$r>1\rightarrow$ s shape
		$r=1\rightarrow$ linear ("rational")

[2] As mentioned above, the curvature of the value function is not sufficient to determine the overall risk aversion, neutrality, or seeking of the individual.

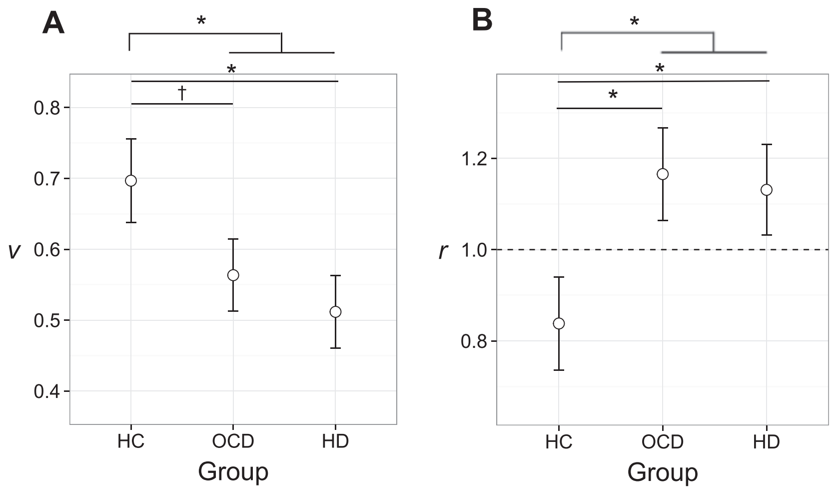

Fig. 3. Group differences in risk preferences. A, Group means of ν parameter estimates. Larger values of ν correspond to greater degrees of risk aversion. B, Group means of r parameter estimates. $r = 1$ corresponds to linear ("rational") probability weighting; error bars represent S.E.M. *p < 0.05, † p<0.10.

the inverse-s shape that is typical of HC, with overweighting of small probabilities and underweighting of large probabilities. When r is greater than one, the curve is s-shaped, meaning that small probabilities are underweighted and large probabilities are overweighted.

2.5. Data analysis

The CPT model was fitted to each participant's data using maximum likelihood estimation (MLE), assuming a logistic choice function (see Supplemental Material for details). This yielded separate estimates of ν and r for each participant. We also pooled the data across participants within each group, yielding a single estimate of ν and r for each group. Next, we used the resulting ν and r parameter estimates as variables in statistical analyses related to group membership and clinical scales. These analyses were carried out using the R statistical package, version 3.1.1 (R Core Team, 2014). Demographic and clinical characteristics were compared across groups using ANOVA. We tested for main effects of group membership on parameter values using ANCOVA (including age as a covariate given group differences), with HD and OCD as a combined patient group and separately. Follow-up pairwise comparisons were estimated using t-tests with pooled standard deviations. Multivariate regression analyses were used to test whether PWF parameters predicted clinical measures in the relevant samples: OCD symptom severity (YBOCS) was examined in the OCD group; hoarding severity (UHSS, SI-R subscales) was examined in the HD group; as the SI-R measures hoarding symptoms in both HD populations and in non-clinical populations, it was examined in all three groups (HD, OCD, and HC), as were depression severity (BDI) and anxiety severity (BAI). The potential influence of psychotropic medication was tested by repeating the analyses with medication status as a covariate.

3. Results

Supplemental Table S1 displays demographic characteristics for our participant samples. The groups differed significantly by age ($p < 0.01$): The HD group was older than the HC group ($p < 0.01$), which was older than the OCD group ($p < 0.01$). Of OCD subjects, 59% suffered from comorbid MDD or Dysthymic disorder and 41% from a co-occurring anxiety disorder. Of HD subjects, 60% suffered from comorbid MDD or Dysthymia and 53% from a co-occurring anxiety disorder. 65% of subjects in the OCD group and 40% of subjects in the HD group reported taking standard antidepressant and/or anxiolytic medications (at stable doses for at least 2 months) at the time of the study.

Mean parameter values are plotted by group in Fig. 3. The combined patient group was characterized by a lower ν parameter (mean = 0.54, standard error of the mean (SEM) = 0.04; $p < 0.05$) and a greater r parameter (mean = 1.15, SEM = 0.07; $p < 0.05$), relative to HC (r: mean = 0.84, SEM = 0.10; ν: mean = 0.70, SEM = 0.06), controlling for age. When OCD and HD were separated, a significant main effect of group was observed for the ν ($p < 0.05$) parameter, with a statistical trend for the r parameter ($p = 0.07$). Follow-up pairwise comparisons revealed that the r parameter was smaller for HC relative to HD (mean = 1.13, SEM = 0.10; $p = 0.04$) and OCD (mean = 1.17, SEM = 0.10; $p = 0.03$), while the HD and OCD groups were statistically indistinguishable ($p = 0.81$); the ν parameter was greater for HC relative to HD (mean = 0.51, SEM = 0.05; $p < 0.05$), and OCD (trend) (mean = 0.56, SEM = 0.05; $p = 0.09$), with no difference between HD and OCD ($p = 0.50$). We did not find a significant effect of group membership on the logistic choice function parameter ($p > 0.10$).[3] Analyses of pooled data yielded ν parameter estimates of 1.0, 0.95, and 0.68, and r parameter estimates of 0.53, 1.24, and 7.64 for HC, OCD, and HD, respectively. Medication status was not a significant predictor of either of the CPT parameters (r: $p > 0.8$; ν: $p > 0.4$), nor did inclusion of medication status as a covariate alter the parameter estimates appreciably. Regression results are displayed in Table 2. The r parameter was a significant predictor of hoarding severity as measured by the UHSS ($p < 0.001$) and SI-R ($p < 0.05$) in individuals with HD. Both parameters were significant predictors of scores on the Difficulty Discarding subscale of the SI-R in HD (r: $p < 0.01$; ν: $p < 0.05$), with statistical trends for the Clutter subscale (r: $p = 0.07$; ν: $p < 0.10$); Acquisition subscale scores were predicted by the r parameter ($p < 0.05$). In the OCD group, both parameters were significant predictors of YBOCS compulsion subscores (r: $p < 0.001$;

[3] To further address the concern that estimates of the ν parameter may tradeoff with the logistic choice function parameter, we computed correlation coefficients between estimated subject-level parameters within each group, and for all subjects. They are reported in Supplemental Table S4. Across the full sample, none are significantly different from zero by a t-test ($p > 0.10$). Scatterplots of the subject-level parameter estimates are shown in Supplemental Figure S1. See Supplemental Material for further details.

Table 2
Multivariate regression models predicting clinical measures.

Predictors	BDI	YBOCS[a]	UHSS[b]	SI-R[b]	SI-R[b,c]	SI-R[b,d]
r	−0.11	−0.84***	0.62***	0.51*	0.46**	0.39*
v	−0.28**	−0.47*	−0.42*	−0.46*	−0.35*	−0.20
HC	−0.87***					
R^2	0.30	0.52	0.50	0.38	0.32	0.18

Standardized beta coefficients; *p < 0.05, **p < 0.01, ***p<0.001.
BDI: Beck Depression Inventory; YBOCS: Yale Brown Obsessive Compulsive Scale, Compulsion subscale; UHSS: UCLA Hoarding Symptom Scale; SI-R: Saving Inventory, Revised; HC: Dummy variable identifying healthy controls.
[a] OCD group.
[b] HD group.
[c] Difficulty discarding subscale of SI-R.
[d] Acquisition subscale of SI-R.

v: $p < 0.05$), though not of obsession subscores. The v parameter was a significant predictor of BDI score across all subjects ($p < 0.01$), controlling for health status. Associations between PWF parameters and BAI scores were not significant (r: $p = 0.65$; v: $p = 0.78$).

Though the groups did not differ significantly by IQ ($p = 0.14$), we replicated the ANOVA and regression analyses including IQ as a covariate and found that the results were essentially unchanged (Supplemental Table S2). However, the statistical significance was diminished for two of the effects: the main effect of group for the r parameter ($p = 0.14$), and the beta coefficient on the r parameter variable in the SI-R acquisition subscale regression ($p = 0.09$).

4. Discussion

In this study, we find that our OCD and HD samples exhibited risk attitudes that differed substantially from healthy controls, and the patterns of decision making under risk correlated with symptomatology as measured by standard clinical scales.

4.1. Group differences in PWF parameters

Our approach permitted us to examine risk attitudes from several complementary perspectives. The first is the value of the outcome sensitivity (v) parameter. Based on this measure, the value function exhibited risk aversion for all groups, which is unsurprising given the predominance of risk aversion in the general population (Kahneman and Tversky, 1979). However, contrary to the conventional view, the value function exhibited *less* risk aversion for the HD and OCD groups than for HC.

As expected, the risk preferences of the HC sample were best described by the classic inverse-s-shape PWF (Fig. 4). In contrast, both the OCD and HD samples exhibited an s-shape PWF. This result implies that individuals with either OCD or HD should be much less interested in lottery tickets, disaster insurance, and would be less likely to show the certainty effect, compared to HC.

The PWF shape has strong implications for attitudes towards certainty and impossibility (Gonzalez and Wu, 1999; Tversky and Kahneman, 1992). It is instructive to consider the extreme values of the r parameter. Fig. 2 shows an inverse-s-shape PWF, which approximates a step function ($r = 0.1$). The decision maker with this PWF is insensitive to changes in probability unless they occur near the extremes of certainty and impossibility; all probability values away from the endpoints are discounted equally, as if they belong to a homogenous category that could be referred to simply as “uncertain.” In contrast, the extreme case of the s-shape (Fig. 2, $r = 10$) is flat near the endpoints and steep towards the middle of the interval, implying that changes in probability near the endpoints have very little impact on the decision maker's preferences.

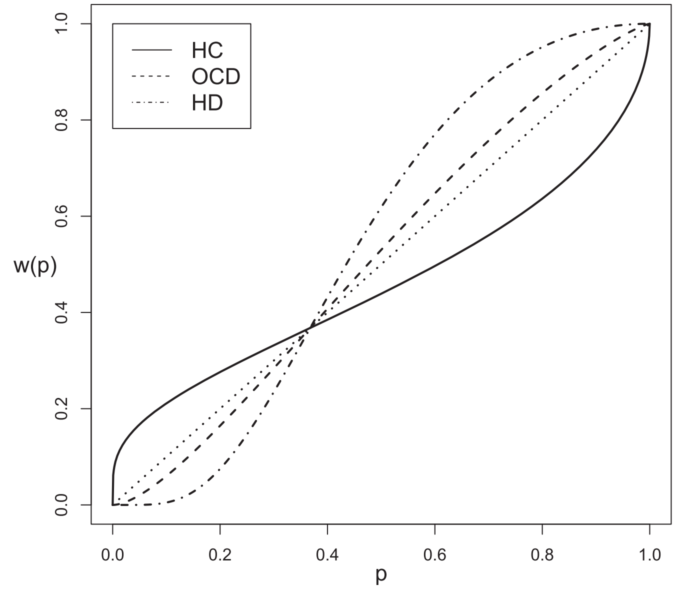

Fig. 4. Probability weighting function plots for the three participant groups based on pooled estimates.

In this case, prospects are essentially perceived in binary terms as either “virtually certain” or “virtually impossible.” For example, a 90% probability of occurrence and a 60% chance of occurrence are weighted equally. Hence, our finding of a greater tendency toward an s-shape PWF among individuals with HD or OCD suggests that these decision makers have a greater tendency to consider prospects in such relatively binary terms, as compared to HC decision makers.

Another prominent interpretation of the PWF holds that portions of the curve that lie above (below) the diagonal imply optimism (pessimism) (Wakker, 1994). It has been argued that the apparent risk-seeking preferences of entrepreneurs actually reflect excessive optimism, rather than a true difference in risk attitude (Weber et al., 2002). On this interpretation, the PWF has less to do with preferences than with outlook. Underweighting (overweighting) implies that one is more pessimistic (optimistic) than is warranted by the objective probability of occurrence. Relative to HC, individuals with HD or OCD would therefore be expected to be more pessimistic about their chance of winning the lottery (low probability), and more optimistic than controls about their chance of obtaining high probability prospects.

Finally, it has been suggested that the curvature parameter of the PWF, r, may be treated as an index of rationality with respect to risky choices, in which case $r = 1$ defines rationality and greater departures from $r = 1$ imply less rational behavior (Tversky and Wakker, 1995). In our study, all three groups were equally irrational in that the average departures from $r = 1$ were statistically indistinguishable for the 3 groups, though in the opposite direction for HC.

4.2. Relationship between PWF parameters and clinical measures

Our findings suggest that risk attitudes may be related to specific patterns of symptomatology. We found an inverse relationship between depressive symptoms and the outcome sensitivity (v) parameter in individuals with OCD or HD. It is worth noting that previous studies of decision making under risk utilizing the IGT in MDD samples have yielded mixed results, with some studies finding greater levels of risk aversion in depressed participants relative to HC, while other studies found the opposite (Ernst, 2012; McGovern et al., 2014).

For participants with OCD, our results suggest that greater compulsion is associated with more rational probability weighting and lower outcome sensitivity parameter values. Within the HD group, we found that hoarding symptoms correlate with *less* rational probability weighting. Analysis of SI-R subscales revealed that difficulty discarding and acquisitiveness, not clutter scores, are likely responsible for this association in HD. Thus it appears that OCD and HD may share certain dimensions of risk attitude (lower outcome sensitivity parameter values) but differ with respect to others (rationality of risk preferences).

The generalizability of our results to clinically familiar situations (e.g., risks associated with discarding belongings in HD or risks of harmful contamination in OCD) depends crucially on the degree to which risk preferences exhibit trait-like stability across time and domains. For example, the results may not be generalizable if risk preferences are domain-specific, such that individuals appear comparatively more risk averse in certain domains (e.g. physical safety) and less risk averse in others (e.g. monetary gains). As mentioned above, there is considerable controversy in the literature regarding the degree of domain-specificity of risk preferences (Einav et al., 2012; Pushkarskaya et al., 2015; Weber et al., 2002; Weber and Johnson, 2009). It is important to note, however, that, regardless of the intuitiveness of the results, the significant correlations between clinical measures and PWF parameters strongly suggest that risk attitudes measured in the monetary domain capture an important hidden variable deserving of further study. In this way, probability weighting may join delay discounting as an economic paradigm with important implications for understanding fundamental cognitive differences between clinical and healthy samples (Glöckner and Pachur, 2012).

As mentioned in above, economists distinguish between risky prospects, in which the relevant probabilities are known or are predictable, and ambiguous prospects, in which the outcome probabilities are unknown; strong evidence exists for the ubiquity of ambiguity aversion in the general population (Camerer and Weber, 1992). Several recent studies found that subjects with OCD had greater ambiguity aversion, but indistinguishable risk preferences, when compared to healthy controls - in clear contrast to our findings (Pushkarskaya et al., 2015; Starcke et al., 2010; Zhang et al., 2015). A possible explanation for the discrepancy is that, with one exception, these studies did not use model-based analyses, and the investigators that did fit a model to their data did not include a probability weighting function, thereby preventing the decomposition of risk attitudes reported here.

In conclusion, using a model-based analysis, we found evidence that individuals with obsessive-compulsive and hoarding disorders have fundamentally different risk attitudes than healthy controls, and that quantitative model parameters are systematically related to specific symptom profiles. As a consequence, risk attitudes may play a role in defining relevant endophenotypes for these disorders. Fruitful extensions of this work may include quantitative comparison of attitudes towards risk and ambiguity in multiple domains, model-based assessment of decision making under risk in other clinical populations, and correlation between risk model parameters and other cognitive constructs in clinical samples.

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Author contributions

G.J. Aranovich and C.A. Mathews designed the study. G.J. Aranovich and D.R. Cavagnaro collected and analyzed the data. All authors contributed to drafting, editing, and developing the manuscript. D.R. Cavagnaro wrote the supplemental material.

Declaration of conflicting interests

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

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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.2017.02.017.

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