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It's All About Gains: Risk Preferences in Problem Gambling

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Problem gambling is a serious socioeconomic problem involving high individual and social costs. In this article, we study risk preferences of problem gamblers including their risk attitudes in the gain and loss domains, their weighting of probabilities, and their degree of loss aversion. Our findings indicate that problem gamblers are systematically more risk taking and less sensitive toward changes in probabilities in the gain domain only. Neither their risk attitudes in the loss domain nor their degree of loss aversion are significantly different from the controls. Additional evidence for a similar degree of sensitivity toward negative outcomes is gained from skin conductance data—a psychophysiological marker for emotional arousal—in a threat-of-shock task.

Keywords: gambling, probability weighting, risk, addiction, skin conductance responses

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Problem gambling is considered to be a public health concern with an average prevalence ranging from 0.5 to 7.6% worldwide (Williams, Volberg, & Stevens, 2012). Reported consequences include financial problems (Moghaddam, Yoon, Campos, & Fong, 2015), social isolation (Trevorrow & Moore, 1998), depression (Clarke, 2006), and suicide (Ledgerwood & Petry, 2004). In this study, we compare the risk preferences of problem gamblers to two types of controls— habitual gamblers and nongambling controls.

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By comparing these three groups, we aim at contributing to our understanding of the behavioral correlates of gambling addiction. But before we outline different psychological mechanisms that potentially explain excessive risk taking observed in gamblers, we give a brief overview of prospect theory, which is currently the most prominent descriptive theory of decision making under risk (Kahneman & Tversky, 1979). This will be the starting point for our analysis and we will discuss hypotheses for gambling addiction and differences among the three groups within this framework. While our study is motivated by prospect theory, the general part of our analysis does not rely on this theory, but it is more generally valid as it relies on an analysis of certainty equivalents.

Prospect theory by Kahneman and Tversky (1979) has three main components: First, outcomes are evaluated relative to a reference point such that positive deviations are coded as gains and negative ones as losses. Second, outcomes in prospect theory are evaluated by a value function v which satisfies diminishing sensitivity and loss aversion. Diminishing sensitivity means that the marginal value is decreasing if one moves further away from the reference point implying a concave (convex) value function in the gain (loss) domain. This assumption accommodates the reflection effect, which summarizes empirical evidence that people are typically risk averse (seeking) for gains (losses). Loss aversion indicates that a given loss has a higher impact on the attractiveness of a lottery than a gain of equal size and is captured by a value function that is steeper for losses than for gains. Finally, probabilities in prospect theory are transformed by a weighting function w: $[0,1] \rightarrow [0,1]$ which is strictly increasing and satisfies $w(0) = 0$ and $w(1) = 1$. Originally, the weighting function was proposed to capture the tendency of people to overweight small and underweight large probabilities. Nowadays, there exists ample evidence that the weighting function is inverse S-shaped for most individuals which besides the overweighting (underweighting) of small (large) probabilities implies a relative insensitivity toward probability changes for medium sized probabilities (Abdellaoui, Bleichrodt, & Paraschiv, 2007; Tversky & Fox, 1995).

Within the prospect theory framework, different psychological mechanisms exist that potentially explain excessive risk taking observed in gambling addiction. First, gambling is typically associated with small probabilities of winning. Gambling addiction might therefore be related to a systematic distorted probability weighting, such that small winning probabilities are more strongly overweighted. This distortion would make gambling more attractive and thus offers an explanation for excessive gambling (Kahneman & Tversky, 1979). Within the framework of prospect theory, this so-called probability distortion hypothesis (Ligneul, Sescousse, Barbalat, Domenech, & Dreher, 2012) would be reflected by a more distorted probability weighting function in the gain domain. Among other things, our approach enables us to study the weighting function in the gain domain and thus allows a direct test of this hypothesis.

Second, gambling addiction might arise from a general upward shift in risk preferences (Ligneul et al., 2012). This theory is supported by empirical evidence showing increased risk taking behavior of problem gamblers in many other domains besides gambling (Powell, Hardoon, Derevensky, & Gupta, 1999; Slutske, Caspi, Moffitt, & Poulton, 2005). This so-called probability elevation hypothesis (Ligneul et al., 2012) would imply that problem gamblers, in general, overweight (underweight) probabilities of gains (losses) over the whole probability range. Within the framework of prospect theory, this hypothesis would express itself in an upward (downward) shifted probability weighting function in the gain (loss) domain. Because we elicit risk preferences in the gain and loss domains, we can test this hypothesis. Ligneul et al. (2012) found empirical support for this hypothesis by analyzing gain-only lotteries with varying probabilities of winning. Because gambling is a decision that involves a trade-off of potential gains and losses considering gains only is not sufficient to conclude that the elevation hypothesis actually drives gambling behavior. This conclusion requires besides the higher elevation in the domain of gains an elevation in the domain of losses which is equal or less for gamblers than for controls. Furthermore, the authors used an unincentivized risk elicitation task. Within the literature, it is still debated as to which extent behavior differs under real versus hypothetical incentives (Kühberger, Schulte-Mecklenbeck, & Perner, 2002). With respect to risk preferences, some studies with representative population samples observe no different behavior under real versus hypothetical incentives (Noussair, Trautmann, & Van de Kuilen, 2013; von Gaudecker, van Soest, & Wengstrom, 2011). Others, by contrast, suggest that behavior is indeed systematically different (Edwards, 1953) and that participants actually apply different choice strategies (Slovic, 1969). Additionally, there is evidence that the brain circuity that is active during real choice is different than under hypothetical choice in many domains (Camerer & Mobbs, 2017). Although this is clearly an important debate, and no consensus or underlying theory has so far been reached, this issue becomes even more important in our case as we study financial risk attitudes of problem gamblers. Traditionally, money has been identified as a main motivator for gambling (Anselme & Robinson, 2013; Schüll, 2012) and it appears implausible that gambling without the thrill of winning/losing money would adequately fulfill a gambler's desires. This statement is supported by studies showing different brain activation during the anticipation and realization of real monetary outcomes in problem gamblers as compared with nongambling controls (Luijten, Schellekens, Kühn, Machielse, & Sescousse, 2017). Following the literature, we randomly choose one lottery for payment at the end of the experiment to provide some real incentives and to make our laboratory experiment more comparable to real-world behavior (Ariely & Norton, 2007).

Finally, problem gamblers might be significantly less loss averse, which refers to the relative steepness of the value function in the loss to the gain domain (Tom, Fox, Poldrack, & Trepel, 2007). We elicit the degree of loss aversion for each participant, which allows us to test this loss aversion hypothesis. Additionally, we record skin conductance responses (SCRs) in a threat-of-shock task to test for differences in sensitivity toward negative outcomes. SCRs describe variations in the electrical properties of the skin caused by sweat secretion. Under sympathetic nervous system activity, sweat gland activity increases and thereby reduces the electric resistance of the skin. Changes in the electrodermal properties of the skin are therefore commonly interpreted as measures of sympathetic and emotional arousal (Boucsein, 1992). Our motivation to include this experiment into our study—although it is based on a different dependent measure (physiological responses vs. choice behavior) and different stimulus (sensory stimulus vs. monetary stimulus)—is thought to increase the robustness of our work for at least two reasons. First, losses are regularly and typically experienced more often than gains during gambling. As outlined in the preceding text, an insensitivity toward losses is a plausible explanation for excessive gambling. From a methodological point of view, however, it is a challenge to simulate real monetary losses in laboratory environments, as participants almost never put their own money at stake. With an initial endowment, it is unclear whether decision making is actually taking place in the loss domain relative to the status quo. Alternatively, physical pain, as done in this study via electric shocks, has been suggested as an appropriate tool to induce real losses in the lab (Berns, Capra, Moore, & Noussair, 2008). Finding converging evidence using monetary and nonmonetary losses should therefore be seen as an indication of robustness of our results. Second, SCRs as markers of emotional arousal have commonly been used to study how individuals perceive risky situations. It has been shown that SCRs are sensitive toward probabilities and magnitudes of outcomes (Berns et al., 2008; Ring & Kaernbach, 2015; Studer & Clark, 2011). Some theories, such as the somatic marker theory (Bechara, Damasio, Tranel, & Damasio, 1997), actually suggest that body signals can have a behavior guiding function. Using SCRs as a dependent variable and finding converging evidence with behavioral measures can therefore be seen as a methodological extension of our work and potentially stimulates further discussions on the relation between somatic signals and behavior in gambling addiction.

The loss aversion hypothesis has been tested in several studies yielding mixed results (Brevers et al., 2012; Gelskov, Madsen, Ramsøy, & Siebner, 2016; Giorgetta et al., 2014; Takeuchi et al., 2015). Although these studies consider both gains and losses by analyzing gambles with a 50/50 chance of winning or losing, they do not control for probability weighting. In gambling decisions, winning and losing probabilities can vary and typically the chances of winning (losing) are smaller (larger) than 50%. Therefore, it appears necessary to additionally control for probability weighting.

The prospect theory model has been applied to explain gambling behavior before. In racetrack betting, for example, it has been shown that horses with high chances of winning are often underbet, whereas horses with low chances of winning are often overbet (Ali, 1977; Griffith, 1949; Weitzman, 1965). Probability weighting seems to be an important driver underlying this observation (Jullien & Salanié, 2000; Snowberg & Wolfers, 2010). Similarly, probability weighting can explain why people tend to buy more lottery tickets as jackpots are increasing even when the absolute chance of winning decreases accordingly (Cook & Clotfelter, 1993). The abovementioned studies apply the prospect theory framework to study gambling behavior and suggest that probability weighting is important. Although these studies analyze the betting behavior of whole markets, our article addresses a different, albeit related, issue, which is a comparison of risk preferences between gamblers versus nongambling controls. In particular, we aim at providing a comprehensive analysis of problem gamblers' risk preferences including the gain and loss domains. Our main findings suggest that gamblers systematically overweight small to medium probabilities of winning, whereas we do not observe any systematic differences in the loss domain. In fact, there is a significant change of behavior observed from the loss to the gain domain in gamblers compared to controls. These findings provide one possible explanation why some individuals persist in gambling activities—despite their severe negative consequences—while the general population does not. The observation that problem gamblers' risk preferences are selectively different from the general population should be considered in behavioral therapies and medical treatment of gambling addiction, as well as in legal regulations of gambling markets. We outline potential applications.

Method

Participants

For the current study, we recruited 74 participants (M_{age} = 38.9 years, SD = 14.7 years). Participants were recruited via advertisements in local newspapers. We had one call which was explicitly targeting regular gamblers and one call which was not. The calls were placed biweekly without any overlap. During the initial phone contact, we informed the potential participants about the general experimental procedure and excluded potential participants on the basis of the following criteria:

- Problematic (illegal) drug consumption, that is, drug consumption at least once a week
- A medically diagnosed history of psychiatric or neurological disorder
- Standard MRI exclusion criteria

Next, participants were invited to the University Hospital in Kiel, Germany, for a semistructured interview (Grant, Steinberg, Kim, Rounsaville, & Potenza, 2004) to evaluate their gambling behavior. The interviews were conducted by certified psychologists and took approximately 30 min. From our sample, 25 participants fulfilled at least three of the *Diagnostic and Statistical Manual of Mental Disorders* (4th ed., text rev; *DSM–IV–TR*; American Psychiatric Association, 2000) criteria for pathological gambling and therefore can be classified as problem gamblers (PG group, four female; Fong et al., 2011; Weintraub et al., 2009). Furthermore, 23 participants were classified as habitual gamblers (HG group, three female). These participants fulfilled fewer than three of the *DSM–IV–TR* criteria but were gambling at least once per week. Additionally, 26 participants, who gambled less than once per month, were recruited as a nongambling control group (C group, five female). All participants gave written informed consent and could decide to discontinue participation at any time. The research protocol was approved by the local ethics committee of the University Hospital in Kiel, and the study was conducted in accordance with the guidelines of the Declaration of Helsinki.

A power analysis indicated that our sample gives us an 87% chance of detecting large differences (d = 0.8) in risk preferences between gamblers and controls using a one-sided Wilcoxon's rank sum test at $p < .050$. Given the fact that we compare extreme cases of behavior—participants with a medically diagnosed addiction to gambling versus nongambling controls—we expect the differences in the main underlying drivers, namely risk preferences, to be large. This assumption is supported by the literature which reports that the effect size (d) of the difference in the elevation of the probability weighting function between problem gamblers and nongambling controls observed by Ligneul et al. (2012) was 0.94. This effect is even larger than the one assumed in the previous power analysis. Assuming this effect size, our sample is adequately large to detect differences in the elevation at $p < .050$ using a one-sided Wilcoxon's rank sum test with a 94% chance. It is worth noting that a meta-analysis reveals an almost large effect size ($d = 0.79$) for stronger delayed reward discounting in problem gamblers than in nongambling controls supporting the view that effect sizes can be expected to be large.

Besides the *DSM–IV–TR* criteria, participants answered the South Oaks Gambling Screen (SOGS; Lesieur & Blume, 1987) to obtain a continuous variable for their gambling behavior. Higher values indicate a higher probability for gambling addiction. As expected, the PG group has the highest mean SOGS score of 8.36 ($SD = 3.82$), followed by the HG group with a mean score of 3.96 ($SD = 2.96$) and the C group with a mean score of 0.42 ($SD = 0.99$). Because the distribution of the SOGS scores in our sample violates the normality assumption (Shapiro–Wilks test, $W = 0.86$, $p < .001$), and we have fewer than 30 observations per group (Moffatt, 2015), a (nonparametric) Kruskall-Wallis test was used to test for significant differences in SOGS scores among the three groups. The test indicates that the groups were significantly different with respect to their SOGS scores, $H(2) = 48.41$, $p < .001$, see Table S1 in the online supplemental material). Post hoc tests after Dunn with Bonferroni correction revealed that all three groups were significantly different ($p < .001$). Following the classification by Bonnaire, Bungener, and Varescon (2017), nine problem gamblers mainly engaged in nonstrategic gambles (lottery, scratch cards or slot machines), three in strategic gambles (horse race betting, sport betting or card games), and 13 in both types of gambles. From our HG group, eight participants mainly engaged in nonstrategic gambles, nine in strategic gambles, and six in both. The PG group in general engaged in a greater variety of gambling types.

All three groups were matched based on characteristics that potentially affect task performance independent of gambling behavior such as demographic variables (age, gender, income, education), and alcohol and cigarette consumption (Kruskall-Wallis tests [$p > .250$]; see Table S1 in the online supplemental material). For the matching, we first recruited a gambler and then aimed at finding a control participant that was as similar as possible in terms of the above outlined variables. This procedure was thought to reduce the risk of other potential confounds as much as possible in our quasi-experimental design. Compared with a larger ($N = 300$) gambling disorder sample from Germany by Wejbera, Müller, Becker, and Beutel (2017), our PG group appears representative in terms of age (our sample: 38.5 ± 15.1 years; Wejbera et al. (2017): 33.3 ± 11.6 years) and gender distribution (our sample: 16% women; Wejbera et al. (2017): 11% women).

After the psychological interview, participants took part in a risk elicitation task, which is described in the next subsection, and a time-preference elicitation task, which is not reported herein. Then, they participated in a threat-of-shock task, which is also outlined in the next subsection. The experimental session concluded with an fMRI experiment, which is not reported herein. The whole procedure took about 3.5 hr.

Risk Elicitation Task

In the experimental task by Vieider, Lefebvre, et al. (2015), participants make repeated decisions between binary monetary lotteries and different sure monetary outcomes. The task elicits risk preferences for gain-only, loss-only and for mixed lotteries. This feature allows us to study risk attitudes in the (a) gain and (b) loss domains, (c) probability weighting, and (d) the degree of loss aversion. These four measures are compared across the three groups and tested according to the previously outlined theories on gambling behavior.

In the pure gain (loss) domain, one outcome is positive (negative) whereas the other outcome is typically zero. The magnitude of the first outcome and the winning (losing) probabilities are manipulated over different choice situations. In the gain domain, participants typically choose the lottery for low sure payments. When the sure payment rises, participants switch and start to prefer the sure payment at a certain point. This is the so-called certainty equivalent, that is, the point where the individual is just indifferent between the sure payment and the lottery. In the loss domain, this behavior is reversed, that is, participants typically prefer a small sure loss over the lottery and switch as the small sure loss increases. In order to cover potential losses, participants received an initial endowment that was as large as the largest possible loss. The task has a total of 29 choice situations (14 for gains, 13 for losses, and two for mixed outcomes). In the mixed prospects, participants state a loss that makes them indifferent between playing a 50/50 lottery involving a certain price and the stated loss, or the status quo which equals zero. The original task includes one mixed lottery. We added a second for robustness. Instructions for this task can be found in Vieider, Lefebvre, et al. (2015) or under http://www.ferdinandvieider.com/instructions_English_Euros.pdf and a summary of the used choice situations is available in Table S2 of the online supplemental material. Lotteries where participants had multiple switching points were excluded from the following analysis. This happened in three cases. For the individual payment, one decision was randomly selected and realized for each participant. This is a standard protocol in the literature (Cox, Sadiraj, & Schmidt, 2015). The possible payments for this task ranged from 0 to 40 Euros.

Nonparametric Data Analysis of Risk Preferences

On the basis of procedures suggested by Vieider and colleagues (Vieider, Chmura, et al., 2015; Vieider, Lefebvre, et al., 2015; Vieider et al., 2018; Vieider, Truong, Martinsson, & Khanh, 2013), we normalize certainty equivalents such that values below (above) the objective probability indicate risk aversion (risk seeking) in the gain domain. In the loss domain, this characteristic is reversed. The normalization can be derived mathematically as follows: The experimental design is based on lotteries with two outcomes. We denote these outcomes by x and y such that $|x| > |y| \geq 0$. Now if x and y are either both gains or both losses, according to prospect theory, the utility of lottery P in which you win x with probability p is given by

$$PT(P) = w(p)v(x) + [1 - w(p)]v(y). \tag{1}$$

Assuming a linear value function where $v(x) = x$, we get according to the previous equation

$$CE(P) = w(p)x + [1 - w(p)]y, \tag{2}$$

where $CE(P)$ is the elicited certainty equivalent. Applying a linear value function deserves some further justification. Originally, the value function was proposed to capture the tendency that the marginal value of gains and losses is decreasing with their magnitude, that is, that "[. . .] the difference in value between a gain of 100 and a gain of 200 appears to be greater than the difference between a gain of 1,100 and a gain of 1,200" (Kahneman & Tversky, 1979, p. 278). This form implies that individuals are risk averse for gains and risk seeking for losses. Given the small monetary amounts that are at stake in our experiment, it appears, however, unlikely that the marginal value of money starts declining and plausibly explains risk preferences. In the literature, the value function is often assumed to be linear for moderate stakes (Abdellaoui, Bleichrodt, & L'Haridon, 2008). Additionally, there is evidence that gambling behavior is driven by probability rather than outcome transformations (Snowberg & Wolfers, 2010). Acknowledging these statements implies that introducing a nonlinear value function into our model would only pick up some of the attitudes toward risk that would otherwise be taken up by probability weighting (Vieider et al., 2013; Zeisberger, Vrecko, & Langer, 2012). The resulting estimations would necessarily be less precise (Yaari, 1965; Zeisberger et al., 2012). Therefore, we report our results under the linear value function assumption within the article. Nevertheless, we provide a section on robustness checks. There we show that our results remain stable if we assume a common power value function as suggested by Tversky and Kahneman (1992) of the form $v(x) = x^{\alpha}$ with $\alpha = 0.50$ or 0.75. Additionally, our results are robust if we estimate a full prospect theory model including the aforementioned power value function.

For $y = 0$ equation 2 immediately shows that $w(p) > (<)p$ implies risk seeking (aversion) in the gain domain and risk aversion (seeking) in the loss domain. Solving equation 2 for $w(p)$ yields

$$\frac{CE(P) - y}{x - y} = w(p). \tag{3}$$

In the following, we will call $(CE(P) - y)/(x–y)$ a normalized certainty equivalent. The normalized certainty equivalent equals p in the case of risk neutrality (i.e., $w(p) = p$) whereas it is less than (exceeds) p in the case of risk aversion (seeking) in the gain domain. In the loss domain, this characteristic is reversed. For illustrative purposes, the analysis of the present article will rely on normalized certainty equivalents instead of regular certainty equivalents. Since a higher regular certainty equivalent implies a higher normalized certainty equivalent, this procedure does not involve any assumptions or restrictions. Therefore, this part of the analysis does not rely on prospect theory or the linear value assumption, but it is valid in a very general sense.

For mixed prospects, we calculate the ratio between the potential gain and the elicited loss that makes the participant just indifferent between playing the lottery or the status quo. The point of loss neutrality would be indicated by a ratio of unity, higher values indicate loss aversion, and smaller values indicate loss seeking. Since we have two mixed prospects, we average the two ratios for each participant to get a more stable estimate of their degree of loss aversion.

Parametric Data Analysis of Risk Preferences

Having provided a nonparametric analysis of our data, we fit functional forms to our data. This approach takes the repeated observations into account and thereby allows us a more precise separation of noise from underlying preferences (Vieider, Lefebvre, et al., 2015). This approach is motivated by prospect theory. We use the probability weighting function developed by Prelec (1998)

$$w(p) = e^{-\delta(-\ln p)^{\gamma}}, \tag{4}$$

where δ measures the elevation of the weighting function. Smaller values of δ shift the weighting function upward. γ measures the degree of curvature. Smaller values of γ indicate a more pronounced inverse S-shape (Fox & Poldrack, 2013). We use the confidence intervals (CI) of the fits to see differences among the groups. The algorithm was initialized with values of 0.7 for both δ and γ (Vieider, Lefebvre, et al., 2015). Changing both starting values to 0.3 did not change the results. No additional boundary conditions were applied.

Threat-of-Shock Task

The threat-of-shock task, which we applied in one of our previous studies (Ring & Kaernbach, 2015), has two stages. In the first stage, the probability of receiving an unpleasant electric shock is revealed. In the second stage, which follows after an anticipation phase of 9.7 s, the electric shock is then applied or not accordingly. Detailed information about the task, as well as on the psychophysiological measurement device and the electric shock device can be found in the online supplemental material. It has been shown that SCRs during the anticipation phase increase with the probability of receiving the electric shock (Ring & Kaernbach, 2015). This allows us to test whether there are differences in terms of emotional body reactions in anticipation of negative events among our groups.

Data Analysis

Skin conductance data were analyzed using Ledalab (www.ledalab.de) applying continuous decomposition analysis to disentangle phasic components from tonic activity (Benedek & Kaernbach, 2010). The integrated SCRs (ISCR), which is defined as the time integral of the phasic driver for a relevant time interval, was used as a measure for the phasic electrodermal response to a given stimulus. ISCRs were calculated during the anticipation phase of the above-described task. In order to account for the typical delay in SCRs of about 1.5 s after stimulus presentation (Boucsein, 1992), we focus on the time interval of + 1.5 to + 9.7 s after revealing the shock probability. Because of skewness of skin conductance data, we take the square root of each response (Boucsein, 1992).

Statistical Analysis

Statistical analysis was performed using the computing environment R (R Version 3.3.2 (R Development Core Team, 2016; RStudio Version 0.99.486 (RStudio Team, 2015). Probability weighting functions were fitted using nonlinear least squares regression with the function *nls* of the stats package (R Development Core Team, 2016). Confidence intervals for the two-parameter probability weighting functions were calculated using Monte Carlo simulations with the *predictNLS* function from the propagate package (Spiess, 2014). Random effects ordinary least squares regressions were performed with the function *plm* of the plm package (Croissant & Millo, 2008). Power analyses were performed with G*Power 3 (Faul, Erdfelder, Lang, & Buchner, 2007).

Data Availability

Our stimulus material (threat-of-shock task), data (behavioral and physiological) as well as our R code for statistical analysis and figure/table preparation are publicly accessible at https://osf.io/n45ky/.

Results

Nonparametric Results on Behavioral Risk Preferences

First, we compare the normalized certainty equivalents of the three different groups across decision domains. As outlined in the preceding text, this analysis does not rely on prospect theory. We perform this analysis on the basis of a group comparison as well as on SOGS scores. Figure 1 shows normalized certainty equivalents by probability of winning for the three different groups. At the smallest probability of winning (*prob* $=$ .125), all three groups have a normalized certainty equivalent which is larger than the objective probability (the objective probability is marked by a black horizontal line). This suggests risk seeking behavior at this particular probability level. With increasing objective probabilities of winning, participants, on average, become risk neutral and finally risk averse. The points where the different groups switch to risk avoiding behavior are different (C group: *prob* $>$ .250; HG group: *prob* $>$ .500; PG group: *prob* $>$ .625).

Now, we can test whether the elicited certainty equivalents are different among the three groups and whether there are differences in the weighting of probabilities. To do so, we run random effects ordinary least squares regressions. This approach allows us to enter the probability level as an independent variable and thereby to control for within-subject differences in probability weighting (Moffatt, 2015; Vieider, Lefebvre, et al., 2015). A detailed description of this method is provided by Moffatt (2015). Table S3 in the online supplemental material displays the result for an analysis where we compare the PG and HG group to the C group. As displayed in Regression I, the PG group is significantly more risk taking than the C group, which is indicated by a positive and significant coefficient for PG group ($\beta = 0.126$, $SE = 0.039$, $p = .001$). The coefficient for HG group is also positive, but smaller than the coefficient for PG group and not significant ($\beta = 0.053$, $SE = 0.040$, $p = .187$). Furthermore, the analysis shows that the significant probability coefficient is smaller than unity indicating probability insensitivity in the overall sample ($\beta = 0.641$, $SE = 0.025$, $p < .001$). This finding was expected and also previously reported (Vieider, Lefebvre, et al., 2015). In order to test whether there are differences in probability weighting among the three groups, Regression II adds an interaction term for the group classification and probability. The interaction term for the PG group is negative and significant indicating that the PG group is significantly more insensitive toward changes in probabilities than the C group ($\beta = -0.307$, $SE = 0.058$, $p < .001$). For the HG group the interaction term is negative, but not significant ($\beta = -0.045$, $SE = 0.060$, $p > .250$). Altogether this analysis shows that the PG group is both more risk taking and less sensitive toward changes in probability than the C group in the gain domain.

As a robustness check, we average the normalized certainty equivalents per participant and probability level, and compare all groups by means of Kruskall-Wallis tests (uncorrected for multiple testing) for

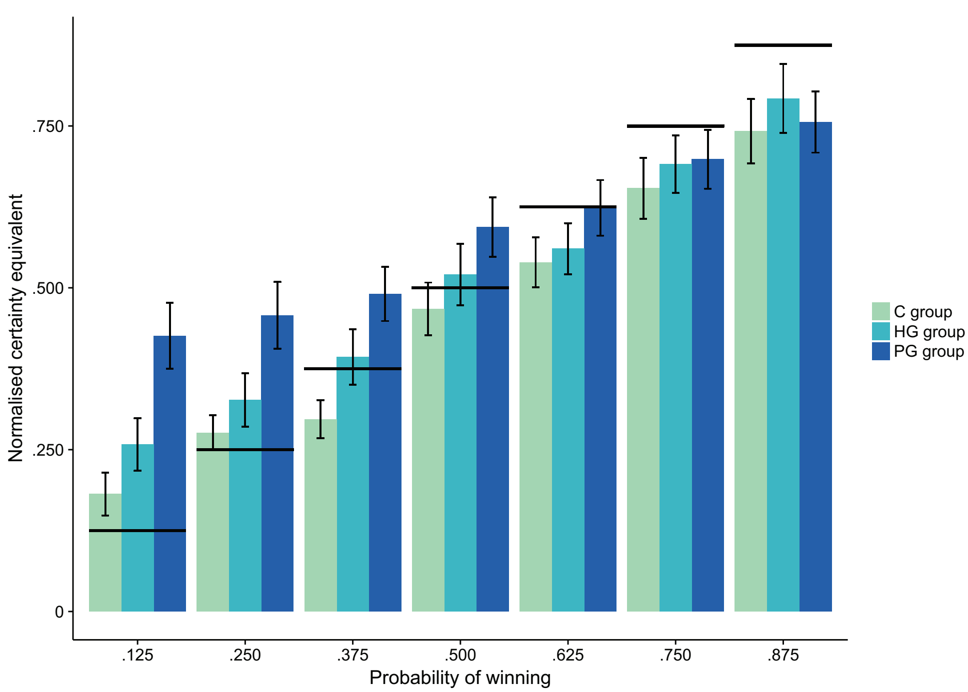

Figure 1. Risk preferences in the gain domain by probability and group. Error bars indicate the standard errors of the mean. Black horizontal lines indicate risk neutrality. If the normalized certainty equivalent is above the black horizontal line, this indicates risk seeking. If the normalized certainty equivalent is below the black horizontal line, this indicates risk aversion. See the online article for the color version of this figure.

each probability level. Our results show that the groups are significantly different at $prob \leq .500$ with a significance level of $p < .050$. Exact p values for the Kruskall-Wallis tests and p values for subsequent post-hoc tests after Dunn are reported in Table 1.

In Table S4 in the online supplemental material, we regress the normalized certainty equivalents on SOGS scores. Regression I reveals that individuals with higher SOGS scores are more risk taking, which is indicated by a positive and significant coefficient for SOGS scores ($\beta = 0.010$, $SE = 0.004$, $p = .008$). Furthermore, Regression II includes an interaction term for SOGS scores and probability. The coefficient is significant and negative ($\beta = -0.016$, $SE = 0.006$, $p = .007$), which suggests that individuals with higher SOGS scores are less sensitive toward changes in probabilities. In a nutshell, this analysis reveals that individuals with higher SOGS scores are more risk taking and less sensitive toward changes in probability. The analysis on the group level and the analysis based on SOGS scores support each other. This was somehow expected, because SOGS scores and a classification based *DSM–IV–TR* criteria have a high positive correlation (Stinchfield, 2002).

Figure 2 shows normalized certainty equivalents by probability of losing for the three different groups. The normalized certainty equivalents can be understood as insurance premia, because they are payments to avoid playing a lottery with a potential monetary loss. The interpretation in the loss domain is thus reversed relative to the gain domain, that is, normalized certainty equivalents that are above (below) the objective probabilities now indicate risk avoiding (risk seeking) behavior. As reported by Vieider, Lefebvre, et al. (2015) and consistent with the reflection effect by Kahneman and Tversky (1979), we find risk aversion for the lowest probability ($prob = .125$) in all three groups. As the probability of losing increases, risk aversion decreases and at some point each group, on average, is risk seeking. A visual inspection of the data does not indicate systematically different patterns among the groups.

Table S5 in the online supplemental material displays the result for an analysis comparing the PG and HG group to the C group in the loss domain. In Regression I, we observe a general insensitivity toward changes in probability in the overall sample. This is revealed by a significant coefficient for probability which is smaller than unity ($\beta = 0.680$, $SE = 0.025$, $p < .001$). Neither the PG nor the HG group is significantly different in terms of their risk attitudes, which is indicated by nonsignificant coefficients for PG group ($\beta = -0.032$, $SE = 0.035$, $p > .250$) and HG group ($\beta = -0.016$, $SE = 0.036$, $p > .250$). In Regression II, an interaction term is added for group classification and probability. The PG group is not significantly different in terms of their probability weighting than the C group ($\beta = -0.108$, $SE = 0.061$, $p = .076$), while the HG group is ($\beta = -0.150$, $SE = 0.063$, $p = .017$). We do not want to overinterpret this finding, because if it is a component of gambling addiction, we would expect a more pronounced effect in the PG group, which we did not observe here.

As a robustness check, we average the normalized certainty equivalents per participant and probability level, and compare all groups by means of Kruskall-Wallis tests (uncorrected for multiple testing) for each probability level. We do not observe statistically significant differences ($p > .200$). Exact p values for the Kruskall-Wallis tests can be found in Table 2. As none of the Kruskall-Wallis tests is significant at the conventional level of $p < .050$, we do not report any post-hoc tests.

The analysis is repeated using SOGS scores as a continuous variable for gambling behavior (see Table S6 in the online supplemental material). We observe a general pattern of probability insensitivity ($\beta = 0.680$, $SE = 0.025$, $p < .001$), but normalized certainty equivalents are neither affected by SOGS scores ($\beta = -0.005$, $SE = 0.003$, $p = .133$) nor by the interaction of SOGS scores and probability ($\beta = -0.002$, $SE = 0.006$, $p > .250$). Altogether we do not observe systematic differences in risk attitudes in the loss domain related to gambling behavior.

In the next step, we analyze the differential risk taking behavior in the gain versus loss domain in the three groups, that is, we analyze how groups change their behavior once they move from one domain to the other. To do so, we introduce an interaction term between group and decision domain (gains vs. losses) in Table S7 of the online supplemental material. Because we did not observe systematic differences in the loss domain, we use this domain as the baseline and analyze how the groups change their behavior from this baseline. First of all, we observe that normalized certainty equivalents for the C group, on average, are significantly smaller in the gain than in the loss domain ($\beta = -0.064$, $SE = 0.016$, $p < .001$). This finding suggests that the C group, on average, is more risk averse in the gain than in the loss domain. Looking at the marginal effects from linear combinations of the parameters and testing them against zero, we observe the opposite effect for the PG group (Domain_Gain + PG group: Domain_Gain = −0.064 + 0.157 = 0.093, $SE = 0.016$, $p < .001$). This indicates that the PG group, on average, is more risk taking in the gain than in the loss domain. For the HG group, the marginal effect is close to zero and not significantly different from zero (Domain_Gain + HG group: Domain_Gain = −0.064 + 0.069 = 0.005, $SE = 0.017$, $p > .250$) suggesting that this group shows similar risk behavior, on average, in the gain and loss domains. Overall, we find evidence for differential risk behavior between the gain versus loss domain in our three groups. These findings are replicated using SOGS scores ($\beta = 0.015$, $SE = 0.002$, $p < .001$) in Table S8 in the online supplemental material.

Finally, we look at the normalized risk preferences for mixed prospects (see Figure S1 in the online supplemental material). The average ratio of the potential gain to the potential loss is greater than unity which indicates loss aversion in all three groups. As the distribution of the loss aversion parameters in our sample violates the normality assumptions (Shapiro-Wilk test, $W = 0.91$, $p < .001$), we used a (nonparametric) Kruskall-Wallis test to identify

Table 1
Kruskall-Wallis Tests and Subsequent Post-Hoc Tests After Dunn for Different Probability Levels in the Gain Domain

Objective probability	Overall p	PG vs. C	PG vs. HG	C vs. HG
.125	<.001	<.001	.017	.104
.250	.021	.006	.090	.326
.375	.001	<.001	.062	.081
.500	.013	.003	.121	.186
.625	.197			
.750	.713			
.850	.514			

Note. PG = problem gamblers group; C = control group; HG = habitual gamblers group. Blank cells indicate that no post-hoc tests were performed as the main test was not statistically significant.

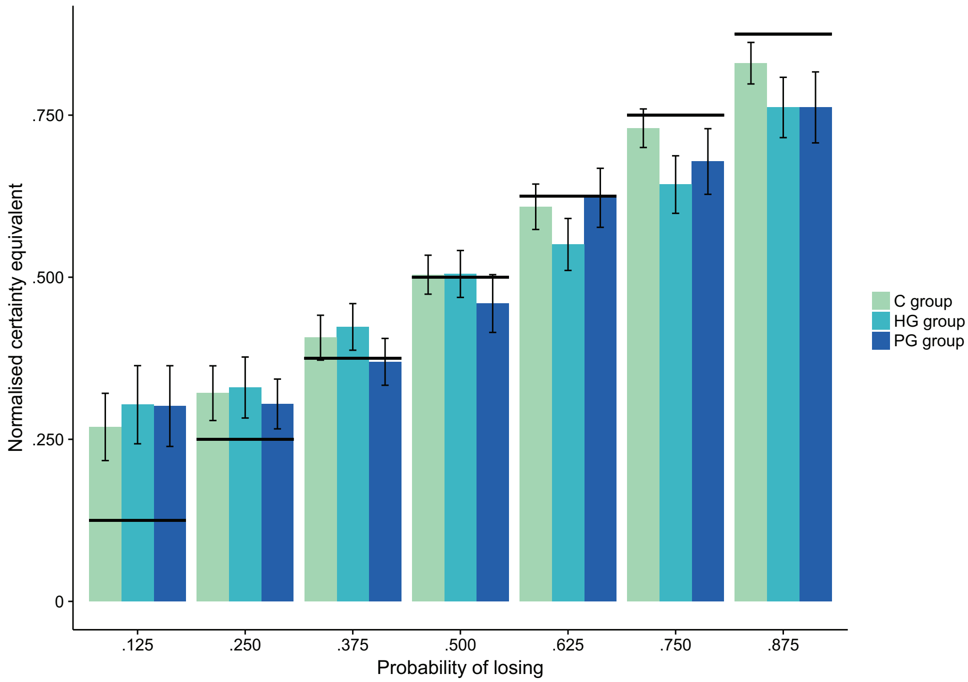

Figure 2. Risk preferences in the loss domain by probability and group. Error bars indicate the standard errors of the mean. Black horizontal lines indicate risk neutrality. If the normalized certainty equivalent is above the black horizontal line, this indicates risk aversion. If the normalized certainty equivalent is below the black horizontal line, this indicates risk seeking. See the online article for the color version of this figure.

significant differences among the groups. This test did not reveal significant differences among the groups, $H(2) = 2.94$, $p = .230$. The conclusion remains the same when we look at the ordinary least squares regression based on SOGS scores in Table S9 in the online supplemental material, as the coefficient for SOGS scores is not significant ($\beta = 0.006$, $SE = 0.020$, $p > .250$), or on a regression based on a group comparison in Table S10 in the online supplemental material where the group coefficients are not significant (HG group: $\beta = -0.309$, $SE = 0.214$, $p = .153$; PG group: $\beta = 0.084$, $SE = 0.203$, $p > .250$)

Parametric Results on Behavioral Risk Preferences

In the next step, we look at results for the parametric fits based on Prelec's probability weighting function. The results for the C group in the gain domain are within the expected range with a mean of 1.02 (95% CI [0.95, 1.09]) for δ and an average value of 0.67 (95% CI [0.57, 0.77]) for γ (Fox & Poldrack, 2013). By looking at the 95% CIs, we see that the PG group has a smaller average value of δ ($M = 0.63$, 95% CI [0.58, 0.69]) than the HG ($M = 0.86$, 95% CI [0.79, 0.93]) and C group. This indicates that the weighting function in the gain domain is shifted upward. There seems to be a decreasing trend from the C group over the HG group to the PG group as displayed in Figure S2. The γ value is also smaller for the PG group ($M = 0.43$, 95% CI [0.32, 0.54]) than for the HG ($M = 0.65$, 95% CI [0.54, 0.77]) and C group which reflects a more pronounced inverse S-shape of the weighting function, that is, a more distorted probability weighting. In Figure 3 we show a graphical representation of Prelec's probability weighting function in the gain domain based on the fitted parameters. Both the upward shift and the more distorted probability weighting are visible. We repeat this analysis for the loss domain. As expected based on the nonparametric analysis, we observe large overlaps of the CIs for both δ and γ among the three groups (see Figure S3). This indicates that also in this analysis no systematically different patterns of risk preferences in the loss domain can be observed. In Figure 4 we show a graphical representation for Prelec's probability weighting function in the loss domain based on the fitted parameters.

Table 2
Kruskall-Wallis Tests and Subsequent Post-Hoc Tests After Dunn for Different Probability Levels in the Loss Domain

Objective probability	Overall *p*	PG vs. C	PG vs. HG	C vs. HG
.125	.909			
.250	.981			
.375	.726			
.500	.407			
.625	.297			
.750	.233			
.850	.499			

Note. PG = problem gamblers group; C = control group; HG = habitual gamblers group. Blank cells indicate that no post-hoc tests were performed as the main test was not statistically significant.

Robustness Checks

We provide several robustness checks for our results. First, we fit the probability weighting function by Lattimore, Baker, and Witte (1992) instead of the probability weighting function by

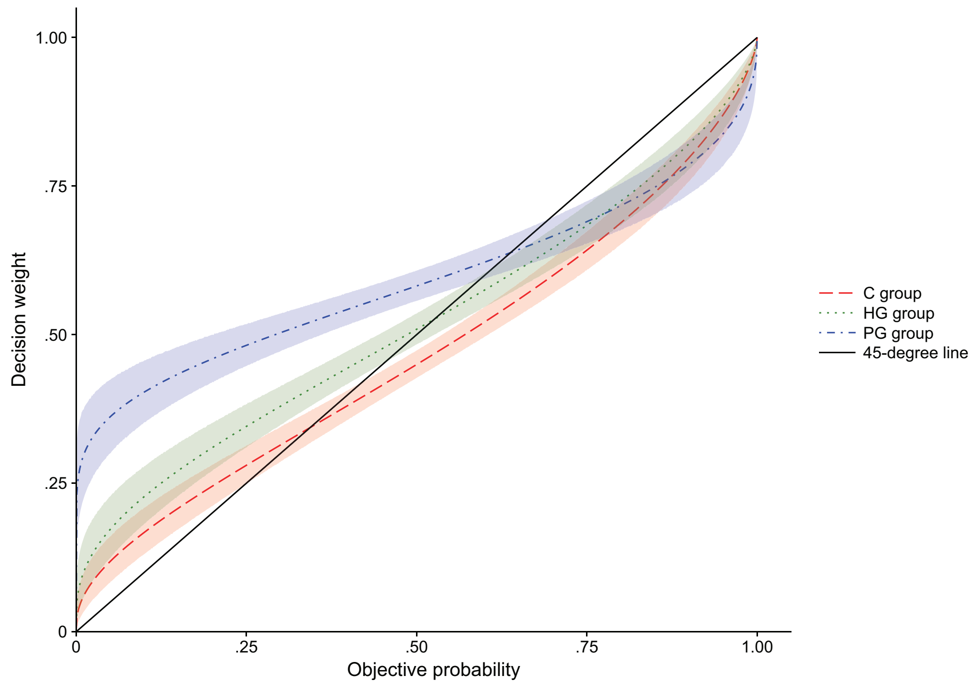

Figure 3. Fitted probability weighting functions by Prelec in the gain domain. Shaded areas indicate the 95% confidence intervals. See the online article for the color version of this figure.

Prelec (1998). This was done to make our results comparable to the study by Ligneul et al. (2012) and to show that our results are robust in regard to the different parametrization. The conclusions drawn from this analysis are in line with our approach and therefore are not reported herein.

Second, we repeat the whole analysis using a common power value function as suggested by Tversky and Kahneman (1992) of the form $v(x) = x^{\alpha}$ with $\alpha = 0.50$ or 0.75. The conclusions drawn from this analysis are the same as under the linear value assumption suggesting that our results do not hinge

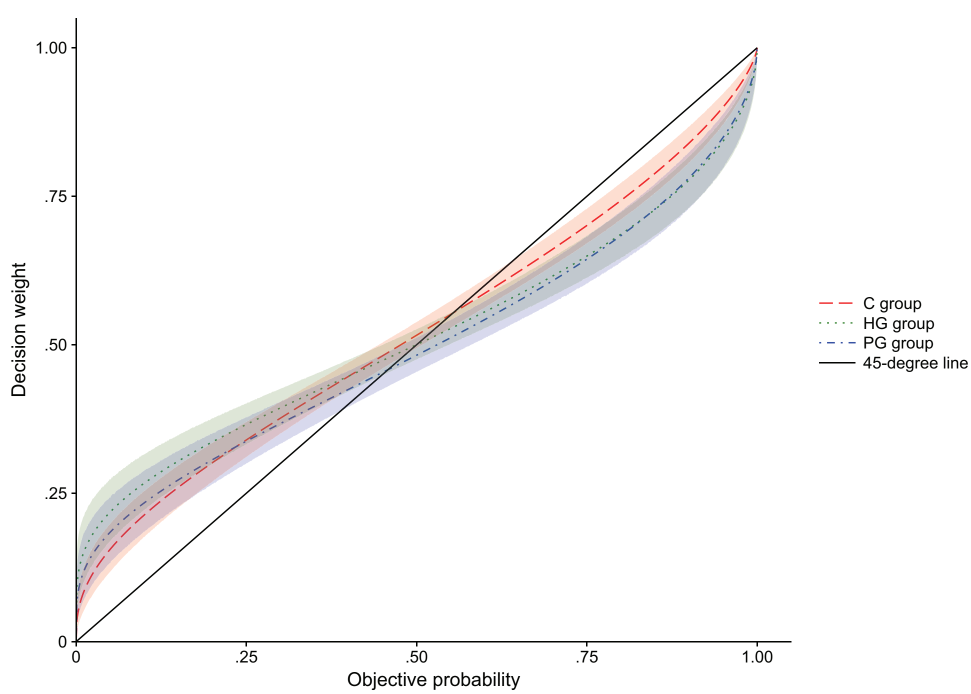

Figure 4. Fitted probability weighting functions by Prelec in the loss domain. Shaded areas indicate the 95% confidence intervals. See the online article for the color version of this figure.

on this particular assumption, but are more generally valid.

Still, it could be that differences in the value function among our groups explain at least partially our results. Therefore, we estimate the full prospect theory model with probability weighting and the value function from above. In the gain domain, we observe that the PG group has a smaller average value of δ and γ than the C group. The 95% CIs of the estimates do not overlap supporting the view that the PG group has both a shifted upward and more distorted probability weighting function in the gain domain. The 95% CIs of the estimates for the α parameter of the value function overlap for all three groups and no systematic difference is visible. In the loss domain, the 95% CIs of the estimates heavily overlap for all parameters of interest and groups suggesting no systematic differences. This translates into probability weighting functions including the 95% CIs that are clearly overlapping over the whole probability space. The results can be found as Figures S4 to S7 in the online supplemental material.

In a nutshell, our results remain stable, although admittedly the estimates became less precise which is indicated by larger confidence intervals. This finding, however, is not surprising because the value function will pick up some of the preferences for risk, which are otherwise taken up by the probability weighting function. This collinearity was ex ante anticipated and refrained us from estimating the whole prospect theory model from the beginning.

Psychophysiological Results From the Threat-of-Shock Task

Figures 5 to 7 show the time course of the phasic driver response during the anticipation phase clustered by shock probability (*prob* $< .250$: low; otherwise: high; Figure 5 for the C group, Figure 6 for the PG group and Figure 7 for the HG group). ISCRs by shock probability for all three groups are available in the online supplemental material as Figure S8. The findings are similar to our previous study (Ring & Kaernbach, 2015) and show higher electrodermal activity for higher shock probabilities. For the statistical analysis, we run random effects ordinary least squares regressions. This approach allows us to control for within-subject differences in reaction to shock probabilities and habituation over the course of the experiment. Habituation is often reported in SCRs-experiments (Boucsein, 1992) and it is captured in our analysis by entering the reciprocal of the round number (Rec_round = 1/Round) as an explanatory variable. A positive coefficient on this variable will indicate an habituation effect.

The statistical analysis of the data on the group level in Table S11 in the online supplemental material reveals that ISCRs increase with the probability of receiving an electric shock, which is indicated by a positive and significant coefficient for shock probability ($\beta = 0.770$, $SE = 0.060$, $p < .001$). Additionally, ISCRs decrease over the course of the experiment, which is indicated by the significant and positive coefficient for Rec_round ($\beta = 0.814$, $SE = 0.066$, $p < .001$). We do not observe statistically significant differences between the C and the HG group ($\beta = 0.121$, $SE = 0.142$, $p > .250$) or the C and the PG group ($\beta = -0.033$, $SE = 0.140$, $p > .250$). The interaction term between shock probability and PG group is also not significant ($\beta = 0.058$, $SE = 0.146$, $p > .250$). We repeat the analysis based on SOGS scores in Table S12 in the online supplemental material. The conclusions remain the same in the sense that there is no systematic relation between

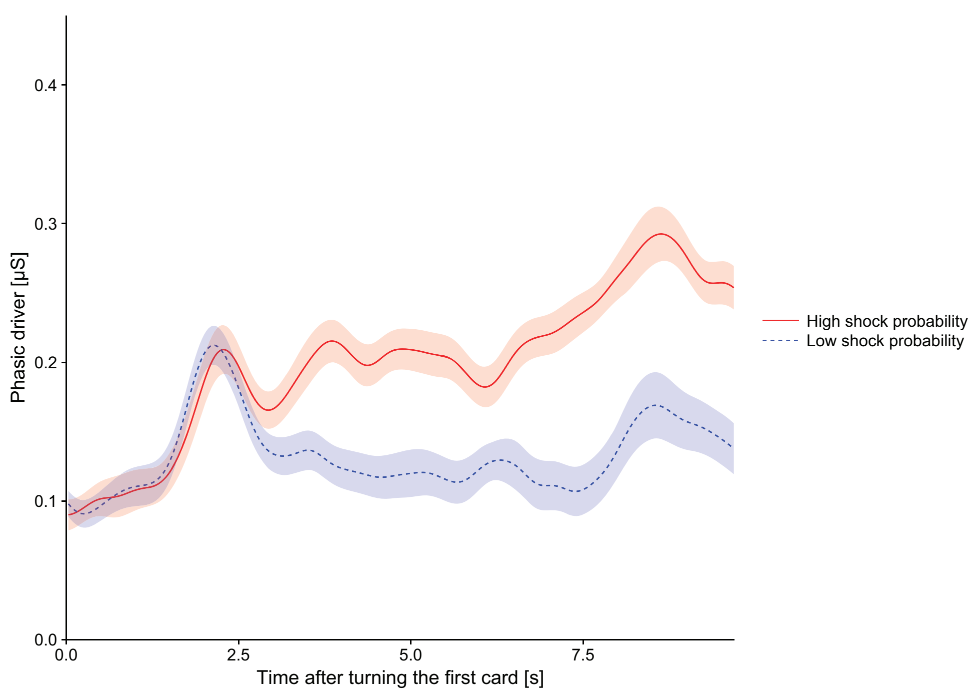

Figure 5. Phasic driver by shock probability for the control (C) group. Shaded areas indicate the standard errors of the mean. See the online article for the color version of this figure.

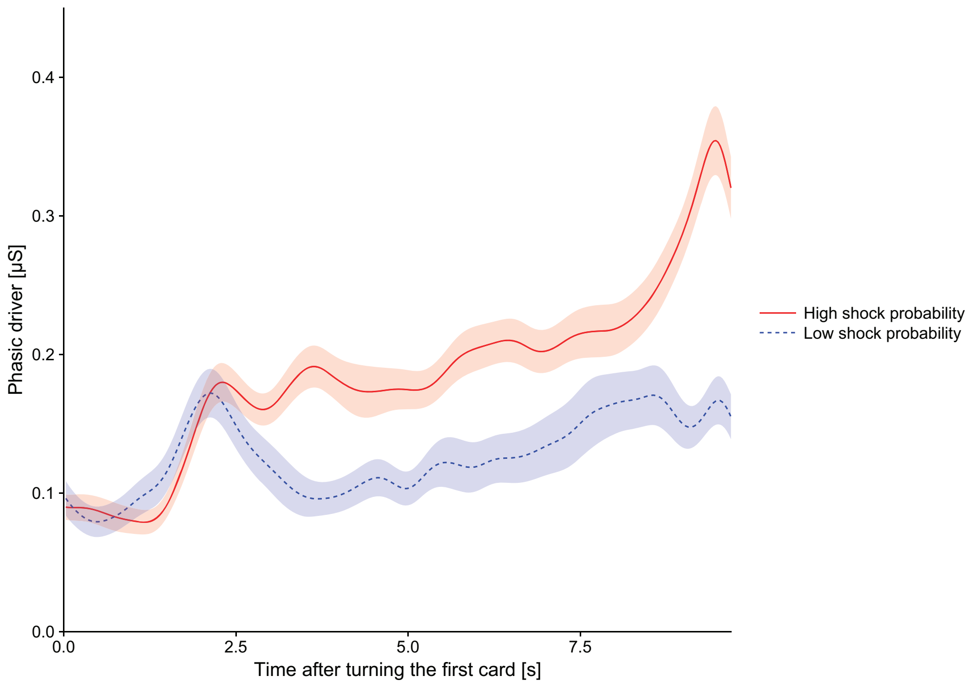

Figure 6. Phasic driver by shock probability for the problem gambler (PG) group. Shaded areas indicate the standard errors of the mean. See the online article for the color version of this figure.

ISCRs and gambling behavior, as the coefficients for SOGS scores ($\beta = -0.002$, $SE = 0.013$, $p > .250$) and for the interaction between SOGS scores and probability ($\beta = 0.013$, $SE = 0.014$, $p > .250$) are nonsignificant.

Although the findings from our two tasks are based on different measures (physiological responses vs. choice behavior) and different stimuli (sensory stimulus vs. monetary stimulus), they both point toward a similar degree of sensitivity toward losses. This

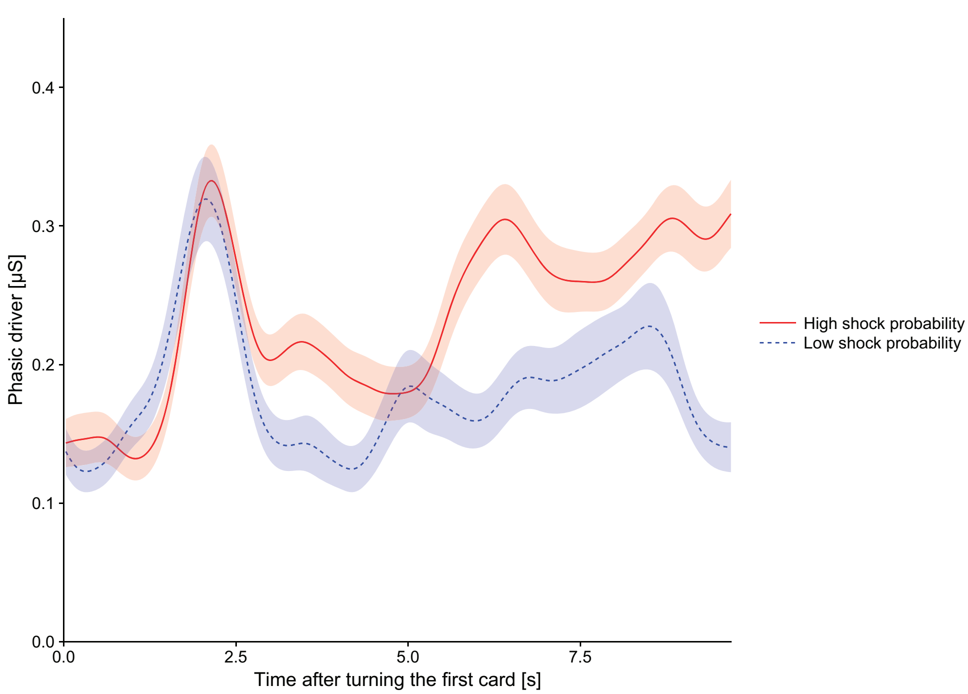

Figure 7. Phasic driver by shock probability for the habitual gamblers (HG) group. Shaded areas indicate the standard errors of the mean. See the online article for the color version of this figure.

finding appears relevant with respect to theories suggesting a direct link between somatic signals and behavior, such as the somatic marker theory by Damasio and colleagues (Bechara et al., 1997). Because we look at SCRs in a passive situation, we cannot make any direct statement about active decision making. Nevertheless, the findings from the two tasks support each other and it is worth noting that we observe a significant negative correlation between the increase in ISCRs for high shock probabilities compared to low shock probabilities, and the normalized certainty equivalents in the loss domain (Pearson's correlation: $r(71) = -.24$, $p = .041$). This exploratory finding indicates a link between the physiological reactions in the threat-of-shock task, and the behavioral risk measures supporting the idea of a similar sensitivity toward negative outcomes for problem gamblers versus controls.

Discussion

Our data reveals that problem gamblers are systematically more risk taking and less sensitive toward changes in probabilities in the gain domain than nongambling controls. This finding holds for a nonparametric comparison that is based on normalized certainty equivalents, but also for a parametric approach that is based on prospect theory. Neither in the loss domain nor for mixed prospects we find systematically different patterns. Furthermore, no statistically significant differences in terms of ISCRs during the anticipation of electric shocks with a varying probability of occurrence were detected.

At the beginning of the article, we outlined three hypotheses that have been brought up to provide an explanation for excessive risk taking observed in gambling addiction within the prospect theory framework. According to the probability distortion hypothesis, problem gamblers have a distorted weighting of winning probabilities, which makes them overly optimistic. The probability elevation hypothesis argues that risk preferences in the gain (loss) domain are generally shifted upward (downward), which makes gambling more attractive but also many other risky activities. Finally, the loss aversion hypothesis states that problem gamblers are less sensitive toward losses relative to gains. Our findings support both the probability distortion and the probability elevation hypothesis, while we do not find evidence for the loss aversion hypothesis. We observe an upward shifted and more distorted probability weighting function, however, only in the gain domain. In the loss domain, we do not find significantly different patterns in risk attitudes. This suggests that the upward shift in the gain domain is neither amplified nor counterbalanced by changes in the loss domain. Our findings hold for a nonparametric group comparison, a nonparametric analysis based on SOGS scores and also for a parametric approach based on the probability weighting function by Prelec.

A limited number of studies has analyzed risk preferences of problem gamblers (Brevers et al., 2012; Gelskov et al., 2016; Giorgetta et al., 2014; Ligneul et al., 2012; Takeuchi et al., 2015). Comparing these studies with ours, we observe three differences in the experimental designs. First, we explore risk preferences including probability weighting for gain-only, loss-only, and mixed prospects. Most existing studies focus on single aspects of the risk attitude space. Although some studies focus on mixed gambles without taking probability weighting into account (Brevers et al., 2012; Gelskov et al., 2016; Giorgetta et al., 2014; Takeuchi et al., 2015), others focus on the gain domain with probability weighting without considering the loss domain (Ligneul et al., 2012). Second, we provide incentives in order to make our findings more comparable to the real world. Some of the aforementioned studies use hypothetical incentives (Brevers et al., 2012; Ligneul et al., 2012; Takeuchi et al., 2015). Third, we include habitual gamblers as an additional control group. This approach allows us to treat gambling addiction as a continuous variable (Strong & Kahler, 2007).

It is important to discuss several limitations of our study. First, we assume a linear value function for all participants. This is a common simplifying assumption within the literature which attributes all variance in risk attitudes to probability weighting (Ligneul et al., 2012; Vieider, Lefebvre, et al., 2015) and thereby avoids potential problems of collinearity between the value and weighting function (Zeisberger et al., 2012). Although it is a common assumption and we also provide several robustness checks, we cannot rule out that differences in the value function between gamblers and nongamblers at larger stakes exist. Therefore, additional research is required which involves significantly higher monetary outcomes and thereby more plausibly elicits participants' attitudes toward wealth. Empirical evidence suggests that relative risk aversion is increasing with stake size in the gain domain (Binswanger, 1980; Fehr-Duda, Bruhin, Epper, & Schubert, 2010; Kachelmeier & Shehata, 1992), whereas the evidence in the loss domain is mixed (Etchart-Vincent, 2004; Fehr-Duda et al., 2010; Hogarth & Einhorn, 1990). Importantly, some studies suggest that changes in risk tolerance due to changes in stake size are not necessarily driven by outcome transformations via the value function, but can be driven by stake dependent probability weights (Fehr-Duda et al., 2010; Kachelmeier & Shehata, 1992). This insight should be taken into account when running large stake studies with problem gamblers. Second, our analysis of loss aversion is based on two observations for each participant, which is lower compared with other studies estimating loss aversion parameters (Sokol-Hessner et al., 2009). Hence, this analysis is necessarily less reliable than our analysis of probability weighting which is based on a larger number of observations. It is important to note, however, that gambling typically does not involve 50/50 gambles and probability weighting appears to be important, as suggested by the literature and our analysis. Third, because of ethical constraints, it is typically not possible that participants gamble with their own money in laboratory experiments. It is necessary to endow participants with money at the beginning of the experiment to study the loss domain (Berns et al., 2008). It is known that this procedure can create a so-called house money effect where participants are more risk seeking because not their own money is at stake (Thaler & Johnson, 1990). We are not aware of any theory suggesting a more or less pronounced house money effect in gamblers, but we cannot rule out the existence of such a tendency. Fourth, the causality of our findings is unclear, that is, whether the probability distortion in the gain domain is the cause or the result of the addiction. With our quasi-experimental design, it is not possible to answer this question and longitudinal studies appear necessary. Understanding the causality underlying our findings would provide significant insights into gambling addiction. Moreover, it is important to mention that problem gamblers can vary a lot in terms of their gambling activities. Although some might prefer gambles with known probabilities, such as roulette, others might prefer gambles where probabilities are less clearly stated, such as horse betting. Because of the different degrees of information involved, it appears interesting for future research not only to study decisions under risk where probabilities are known, but also decisions under ambiguity where probabilities are unknown. Usually, risk and ambiguity preferences are studied separately. In the model by Fox and Tversky (1998), however, ambiguity preferences follow a two-step process of first judging the probability of an ambiguous event and then transforming this probability by the probability weighting function under risk. Under this model, the observed effects here would also impact the decisions under ambiguity. Clearly, more research is needed and particularly on the question whether gamblers self-select themselves into certain types of gambling depending on their attitudes toward risk and/or ambiguity. Furthermore, we tried our best to match gamblers and nongamblers in terms of variables that potentially affect risk preferences independent of gambling addiction. Because of the quasi-experimental design, we cannot completely rule out the existence of potential confounds. For example, it has been shown that migrants are particularly susceptible to gambling problems (Canale et al., 2017). At the same time, there is empirical evidence suggesting that migrants tend to be more risk taking (Balaz & Williams, 2011; Jaeger et al., 2010), although there are different results for Germany (Bonin, Constant, Tatsiramos, & Zimmermann, 2009). We did not record the participants' ethnic background directly, but created an indirect proxy which was based on ratings of their names for a potential foreign background. The ratings were performed by three independent raters and classification was done using a simple majority rule. On the basis of this method, 3 out of 25 problem gamblers, 2 out of 23 habitual gamblers, and 2 out of 26 controls were identified as potentially having a foreign background. Including a dummy for a potential foreign background into our analysis on risk preferences did not change the conclusions, nor did the coefficient become statistically significant in any of the models. Another limitation might be the random lottery mechanism that we use to provide incentives for the risk task. It is important to stress that this procedure is only fully incentive compatible under prospect theory, if participants make each decision in isolation from the other decisions. It is debated to which extent this so-called isolation hypothesis holds (Camerer, 1989; Cox et al., 2015; Starmer & Sugden, 1991). If isolation is violated, there does not exist any incentive compatible elicitation mechanism for prospect theory. We also have to acknowledge that our sample can be considered to be comparatively small according to current scientific standards. As outlined by Button et al. (2013), general problems of studies with small sample size are that they have an increased risk of reporting false negative and false positive results, and may suffer from effect size inflation. The latter shortcoming might potentially affect our power calculations. It is important to mention, however, that we study a group of participants where the recruitment process is particularly challenging for various reasons such as lack of incentives/motivation for participation, or fear of infringement of anonymity (Parke & Griffiths, 2002). Collaborating with treatment facilities as other studies do was not an option for us for the ethical concern of playing lotteries with people who are trying to abstain from gambling. Finally, we observe no statistically significant differences in terms of physiological responses during the anticipation of electric shocks with varying probability of occurrence, and probability weighting in the loss domain between problem gamblers and nongambling controls. Although both findings are based on different measures (physiological responses vs. choice behavior) and different stimuli (sensory stimulus vs. monetary stimulus), they both point toward a similar degree of sensitivity toward losses. This statement is further supported by a significant correlation between the physiological responses and the choice data in the loss domain.

To conclude, we give an outlook to which extent our findings might have medical applications and how they could be taken into account in the legal regulation of gambling markets. Recent studies indicate that the interference with hormonal mechanisms through drugs can have a selective impact on financial risk preferences. Sokol-Hessner et al. (2015), for example, show that propranolol, a beta-blocker, has an effect on loss aversion, but not on risk attitudes. Although this is not the only study suggesting an impact of hormones on decision making (Brunnlieb et al., 2016), it does reveal that hormonal mechanisms potentially affect specific aspects of risk behavior. Within the context of our study, this appears as highly relevant, if one thinks about a medical treatment for gambling addiction (although we observe group differences in risk attitudes and not in loss aversion). More directly related to our findings is a study by Takahashi et al. (2010) showing a relation between striatal dopamine D1 receptor binding and probability weighting. In this regard, it appears crucial to understand both the behavioral and neurobiological mechanisms underlying gambling addiction to develop new therapies.

With respect to implications for the regulation of gambling markets, it is important to note that gambling providers in Germany have several legal obligations including a duty to provide objective information, which is usually realized by stating winning probabilities, potential gains and stake size. At the same time, there is a legal obligation to prevent gambling addiction. From our findings, both goals or how they are currently pursued, appear orthogonal to each other. Because problem gamblers heavily overweight small to medium winning probabilities, they are particularly susceptible to this type of information presentation. Focusing instead on losing probabilities where the probability distortion is clearly less pronounced for problem gamblers, appears as one possibility to better align the two goals stated in the German regulation on gambling markets.

References

Abdellaoui, M., Bleichrodt, H., & L'Haridon, O. (2008). A tractable method to measure utility and loss aversion under prospect theory. *Journal of Risk and Uncertainty, 36,* 245–266.

Abdellaoui, M., Bleichrodt, H., & Paraschiv, C. (2007). Loss aversion under prospect theory: A parameter-free measurement. *Management Science, 53,* 1659–1674.

Ali, M. M. (1977). Probability and utility estimates for racetrack bettors. *Journal of Political Economy, 85,* 803–815.

American Psychiatric Association. (2000). *Diagnostic and statistical manual of mental disorders* (4th ed., text rev.). Washington, DC: Author.

Anselme, P., & Robinson, M. (2013). What motivates gambling behavior? Insight into dopamine's role. *Frontiers in Behavioral Neuroscience, 7,* 182.

Ariely, D., & Norton, M. I. (2007). Psychology and experimental economics: A gap in abstraction. *Current Directions in Psychological Science, 16,* 336–339.

Balaz, V., & Williams, A. M. (2011). Risk attitudes and migration experience. *Journal of Risk Research, 14,* 583–596.

Bechara, A., Damasio, H., Tranel, D., & Damasio, A. R. (1997). Deciding advantageously before knowing the advantageous strategy. *Science, 275,* 1293–1295.

Benedek, M., & Kaernbach, C. (2010). A continuous measure of phasic electrodermal activity. *Journal of Neuroscience Methods, 190,* 80–91.

Berns, G. S., Capra, C. M., Moore, S., & Noussair, C. (2008). Three studies on the neuroeconomics of decision-making when payoffs are real and negative. *Advances in Health Economics and Health Services Research, 20,* 1–29.

Binswanger, H. P. (1980). Attitudes toward risk: Experimental measurement in rural India. *American Journal of Agricultural Economics, 62,* 395–407.

Bonin, H., Constant, A., Tatsiramos, K., & Zimmermann, K. F. (2009). Native-migrant differences in risk attitudes. *Applied Economics Letters, 16,* 1581–1586.

Bonnaire, C., Bungener, C., & Varescon, I. (2017). Sensation seeking in a community sample of French gamblers: Comparison between strategic and non-strategic gamblers. *Psychiatry Research, 250,* 1–9.

Boucsein, W. (1992). *Electrodermal activity*. New York, NY: Plenum Press University Press.

Brainard, D. (1997). The Psychophysics Toolbox. *Spatial Vision, 10,* 433–436.

Brevers, D., Cleeremans, A., Goudriaan, A. E., Bechara, A., Kornreich, C., Verbanck, P., & Nöel, X. (2012). Decision making under ambiguity but not under risk is related to problem gambling severity. *Psychiatry Research, 200,* 568–574.

Brunnlieb, C., Nave, G., Camerer, C. F., Schosser, S., Vogt, B., Münte, T. F., & Heldmann, M. (2016). Vasopressin increases human risky cooperative behavior. *Proceedings of the National Academy of Sciences of the United States of America, 113,* 2051–2056.

Button, K. S., Ioannidis, J. P., Mokrysz, C., Nosek, B. A., Flint, J., Robinson, E. S., & Munafò, M. R. (2013). Power failure: Why small sample size undermines the reliability of neuroscience. *Nature Reviews Neuroscience, 14,* 365–376.

Camerer, C. F. (1989). An experimental test of several generalized utility theories. *Journal of Risk and Uncertainty, 2,* 61–104.

Camerer, C. F., & Mobbs, D. (2017). Differences in behavior and brain activity during hypothetical and real choices. *Trends in Cognitive Sciences, 21,* 46–56.

Canale, N., Vieno, A., Lenzi, M., Griffiths, M. D., Borraccino, A., Lazzeri, G., . . . Santinello, M. (2017). Income inequality and adolescent gambling severity: Findings from a large-scale Italian representative survey. *Frontiers in Psychology, 8,* 1318.

Clarke, D. (2006). Impulsivity as a mediator in the relationship between depression and problem gambling. *Personality and Individual Differences, 40,* 5–15.

Cook, P. J., & Clotfelter, C. T. (1993). The peculiar scale economies of lotto. *American Economic Review, 83,* 634–643.

Cox, J. C., Sadiraj, V., & Schmidt, U. (2015). Paradoxes and mechanisms for choice under risk. *Experimental Economics, 18,* 215–250.

Croissant, Y., & Millo, G. (2008). Panel data econometrics in R: The plm package. *Journal of Statistical Software, 27,* 1–43.

Edwards, W. (1953). Probability-preferences in gambling. *American Journal of Psychology, 66,* 349–364.

Etchart-Vincent, N. (2004). Is probability weighting sensitive to the magnitude of consequences? An experimental investigation on losses. *Journal of Risk and Uncertainty, 28,* 217–235.

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G* Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods, 39,* 175–191.

Fehr-Duda, H., Bruhin, A., Epper, T., & Schubert, R. (2010). Rationality on the rise: Why relative risk aversion increases with stake size. *Journal of Risk and Uncertainty, 40,* 147–180.

Fong, T. W., Campos, M. D., Brecht, M.-L., Davis, A., Marco, A., Pecanha, V., & Rosenthal, R. J. (2011). Problem and pathological gambling in a sample of casino patrons. *Journal of Gambling Studies, 27,* 35–47.

Fox, C. R., & Poldrack, R. A. (2013). Prospect theory and the brain. In P. Glimcher & E. Fehr (Eds.), *Neuroeconomics* (2nd ed., pp. 533–567). San Diego, CA: Academic Press.

Fox, C. R., & Tversky, A. (1998). A belief-based account of decision under uncertainty. *Management Science, 44,* 879–895.

Gelskov, S. V., Madsen, K. H., Ramsøy, T. Z., & Siebner, H. R. (2016). Aberrant neural signatures of decision-making: Pathological gamblers display cortico-striatal hypersensitivity to extreme gambles. *NeuroImage, 128,* 342–352.

Giorgetta, C., Grecucci, A., Rattin, A., Guerreschi, C., Sanfey, A. G., & Bonini, N. (2014). To play or not to play: A personal dilemma in pathological gambling. *Psychiatry Research, 219,* 562–569.

Grant, J. E., Steinberg, M. A., Kim, S. W., Rounsaville, B. J., & Potenza, M. N. (2004). Preliminary validity and reliability testing of a structured clinical interview for pathological gambling. *Psychiatry Research, 128,* 79–88.

Griffith, R. M. (1949). Odds adjustments by American horse-race bettors. *American Journal of Psychology, 62,* 290–294.

Hogarth, R. M., & Einhorn, H. J. (1990). Venture theory: A model of decision weights. *Management Science, 36,* 780–803.

Jaeger, D. A., Dohmen, T., Falk, A., Huffman, D., Sunde, U., & Bonin, H. (2010). Direct evidence on risk attitudes and migration. *The Review of Economics and Statistics, 92,* 684–689.

Jullien, B., & Salanié, B. (2000). Estimating preferences under risk: The case of racetrack bettors. *Journal of Political Economy, 108,* 503–530.

Kachelmeier, S. J., & Shehata, M. (1992). Examining risk preferences under high monetary incentives: Experimental evidence from the People’s Republic of China. *American Economic Review, 82,* 1120–1141.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica, 47,* 263–291.

Kühberger, A., Schulte-Mecklenbeck, M., & Perner, J. (2002). Framing decisions: Hypothetical and real. *Organizational Behavior and Human Decision Processes, 89,* 1162–1175.

Lattimore, P. K., Baker, J. R., & Witte, A. D. (1992). The influence of probability on risky choice: A parametric examination. *Journal of Economic Behavior and Organization, 17,* 377–400.

Ledgerwood, D. M., & Petry, N. M. (2004). Gambling and suicidality in treatment-seeking pathological gamblers. *Journal of Nervous and Mental Disease, 192,* 711–714.

Lesieur, H., & Blume, S. (1987). The South Oaks Gambling Screen (SOGS): A new instrument for the identification of pathological gamblers. *American Journal of Psychiatry, 144,* 1184–1188.

Ligneul, R., Sescousse, G., Barbalat, G., Domenech, P., & Dreher, J.-C. (2012). Shifted risk preferences in pathological gambling. *Psychological Medicine, 43,* 1059–1068.

Luijten, M., Schellekens, A. F., Kühn, S., Machielse, M. W., & Sescousse, G. (2017). Disruption of reward processing in addiction: An image-based meta-analysis of functional magnetic resonance imaging studies. *Journal of the American Medical Association Psychiatry, 74,* 387–398.

McElroy, S. L., Keck Jr., P. E., Pope Jr., H. G., Smith, J. M., & Strakowski, S. M. (1994). Compulsive buying: A report of 20 cases. *Journal of Clinical Psychiatry, 55,* 242–248.

Moffatt, P. G. (2015). *Experimetrics: Econometrics for experimental economics*. New York, NY: Palgrave Macmillan.

Moghaddam, J. F., Yoon, G., Campos, M. D., & Fong, T. W. (2015). Social and behavioral problems among five gambling severity groups. *Psychiatry Research, 230,* 143–149.

Noussair, C. N., Trautmann, S. T., & Van de Kuilen, G. (2013). Higher order risk attitudes, demographics, and financial decisions. *Review of Economic Studies, 81,* 325–355.

Parke, J., & Griffiths, M. (2002). Slot machine gamblers—Why are they so hard to study? *Journal of Gambling Issues*. Advance online publication. http://dx.doi.org/10.4309/jgi.2002.6.7

Powell, J., Hardoon, K., Derevensky, J. L., & Gupta, R. (1999). Gambling and risk-taking behavior among university students. *Substance Use and Misuse, 34,* 1167–1184.

Prelec, D. (1998). The probability weighting function. *Econometrica, 66,* 497–527.

R Development Core Team. (2016). *R: A language and environment for statistical computing*. Vienna, Austria: Author.

Ring, P., & Kaernbach, C. (2015). Sensitivity towards fear of electric shock in passive threat situations. *PLOS ONE, 10*(3), e0120989.

RStudio Team. (2015). *Rstudio: Integrated development environment for R*. Boston, MA: Author.

Saß, H., Wittchen, H.-U., Zaudig, M., & Houben, I. (2003). *Diagnostisches und Statistisches Manual Psychischer Störungen—Textrevision*. Göttingen, Germany: Hogrefe.

Schüll, N. D. (2012). *Addiction by design: Machine gambling in Las Vegas*. Princeton, NJ: Princeton University Press.

Slovic, P. (1969). Differential effects of real versus hypothetical payoffs on choices among gambles. *Journal of Experimental Psychology, 80,* 434–437.

Slutske, W. S., Caspi, A., Moffitt, T. E., & Poulton, R. (2005). Personality and problem gambling: A prospective study of a birth cohort of young adults. *Archives of General Psychiatry, 62,* 769–775.

Snowberg, E., & Wolfers, J. (2010). Explaining the favorite–long shot bias: Is it risk-love or misperceptions? *Journal of Political Economy, 118,* 723–746.

Sokol-Hessner, P., Hsu, M., Curley, N. G., Delgado, M. R., Camerer, C. F., & Phelps, E. A. (2009). Thinking like a trader selectively reduces individuals' loss aversion. *Proceedings of the National Academy of Sciences of the United States of America, 106,* 5035–5040.

Sokol-Hessner, P., Lackovic, S. F., Tobe, R. H., Camerer, C. F., Leventhal, B. L., & Phelps, E. A. (2015). Determinants of propranolol's selective effect on loss aversion. *Psychological Science, 26,* 1123–1130.

Spiess, A.-N. (2014). propagate: Propagation of uncertainty (R package version 1.0–4) [Computer software]. Retrieved from http://CRAN.R-project.org/package=propagate

Starmer, C., & Sugden, R. (1991). Does the random-lottery incentive system elicit true preferences? An experimental investigation. *American Economic Review, 81,* 971–978.

Stinchfield, R. (2002). Reliability, validity, and classification accuracy of the South Oaks Gambling Screen (SOGS). *Addictive Behaviors, 27,* 1–19.

Strong, D. R., & Kahler, C. W. (2007). Evaluation of the continuum of gambling problems using the *DSM–IV*. *Addiction, 102,* 713–721.

Studer, B., & Clark, L. (2011). Place your bets: Psychophysiological correlates of decision-making under risk. *Cognitive, Affective and Behavioral Neuroscience, 11,* 144–158.

Takahashi, H., Matsui, H., Camerer, C., Takano, H., Kodaka, F., Ideno, T., . . . Suhara, T. (2010). Dopamine D1 receptors and nonlinear probability weighting in risky choice. *Journal of Neuroscience, 30,* 16567–16572.

Takeuchi, H., Kawada, R., Tsurumi, K., Yokoyama, N., Takemura, A., Murao, T., . . . Takahashi, H. (2015). Heterogeneity of loss aversion in pathological gambling. *Journal of Gambling Studies, 32,* 1143–1154.

Thaler, R. H., & Johnson, E. J. (1990). Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice. *Management Science, 36,* 643–660.

Tom, S. M., Fox, C. R., Poldrack, R. A., & Trepel, C. (2007). The neural basis of loss aversion in decision-making under risk. *Science, 315,* 515–518.

Trevorrow, K., & Moore, S. (1998). The association between loneliness, social isolation and women's electronic gaming machine gambling. *Journal of Gambling Studies, 14,* 263–284.

Tversky, A., & Fox, C. R. (1995). Weighing risk and uncertainty. *Psychological Review, 102,* 269–283.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty, 5,* 297–323.

Vieider, F. M., Beyene, A., Bluffstone, R., Dissanayake, S., Gebreegziabher, Z., Martinsson, P., & Mekonnen, A. (2018). Measuring risk preferences in rural Ethiopia. *Economic Development and Cultural Change*. Advance online publication. http://dx.doi.org/10.1086/696106

Vieider, F. M., Chmura, T., Fisher, T., Kusakawa, T., Martinsson, P., Thompson, F. M., & Sunday, A. (2015). Within-versus between-country differences in risk attitudes: Implications for cultural comparisons. *Theory and Decision, 78,* 209–218.

Vieider, F. M., Lefebvre, M., Bouchouicha, R., Chmura, T., Hakimov, R., Krawczyk, M., & Martinsson, P. (2015). Common components of risk and uncertainty attitudes across contexts and domains: Evidence from 30 countries. *Journal of the European Economic Association, 13,* 421–452.

Vieider, F. M., Truong, N., Martinsson, P., & Khanh, N. P. (2013). *Risk preferences and development revisited: A field experiment in Vietnam*. Discussion Papers, WZB Junior Research Group Risk and Development. Berlin, Germany: Social Science Research Center Berlin. Retrieved from https://ideas.repec.org/p/zbw/wzbrad/spii2013403.html

von Gaudecker, H.-M., van Soest, A., & Wengstrom, E. (2011). Heterogeneity in risky choice behavior in a broad population. *American Economic Review, 101,* 664–694.

Voon, V., Hassan, K., Zurowski, M., De Souza, M., Thomsen, T., Fox, S., . . . Miyasaki, J. (2006). Prevalence of repetitive and reward-seeking behaviors in Parkinson disease. *Neurology, 67,* 1254–1257.

Weintraub, D., Hoops, S., Shea, J. A., Lyons, K. E., Pahwa, R., Driver-Dunckley, E. D., . . . Voon, V. (2009). Validation of the questionnaire for impulsive-compulsive disorders in Parkinson's disease. *Movement Disorders, 24,* 1461–1467.

Weitzman, M. (1965). Utility analysis and group behavior: An empirical study. *Journal of Political Economy, 73,* 18–26.

Wejbera, M., Müller, K. W., Becker, J., & Beutel, M. E. (2017). The Berlin Inventory of Gambling Behavior-Screening (BIG-S): Validation using a clinical sample. *BMC Psychiatry, 17,* 188.

Williams, R. J., Volberg, R. A., & Stevens, R. M. (2012). *The population prevalence of problem gambling: Methodological influences, standardized rates, jurisdictional differences, and worldwide trends*. Retrieved from https://www.uleth.ca/dspace/handle/10133/3068

Yaari, M. E. (1965). Convexity in the theory of choice under risk. *Quarterly Journal of Economics, 79,* 278–290.

Zeisberger, S., Vrecko, D., & Langer, T. (2012). Measuring the time stability of prospect theory preferences. *Theory and Decision, 72,* 359–386.

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