

It's all about gains: Risk preferences in problem gambling

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## Abstract

Problem gambling is a serious socio-economic problem involving high individual and social costs. In this paper, 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 towards 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 towards 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

## It's all about gains: Risk preferences in problem gambling

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 non-gambling controls. 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 towards 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.

Secondly, 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, Haroon, 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 unincitvized risk elicitation task. Within the literature, it is still debated as to which extent behavior differs under real vs. hypothetical incentives (Kühberger, Schulte-Mecklenbeck, & Perner, 2002). With respect to risk preferences, some studies with representative population samples observe no different behavior under real vs. 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 circuitry that is active during real choice is different than under hypothetical choice in many domains (Camerer & Mobbs, 2017). While 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 to non-gambling 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 towards 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. Firstly, losses are regularly and typically experienced more often than gains during gambling. As outlined above, an insensitivity towards 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 non-monetary losses should therefore be seen as an indication of robustness of our results. Secondly, 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 towards 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). While 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, while 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 above-mentioned studies apply the prospect theory framework to study gambling behavior and suggest that probability weighting is important. While these studies analyze the betting behavior of whole markets, our paper addresses a different, albeit related, issue, which is a comparison of risk preferences between gamblers vs. non-gambling 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, while 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 (*mean 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 bi-weekly without any overlap. During the initial phone contact, we informed the potential participants about the general experimental procedure and excluded potential participants based on the following criteria:

- Problematic (illegal) drug consumption, i.e., 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 semi-structured interview (Grant, Steinberg, Kim, Rounsaville, & Potenza, 2004) in order to evaluate their gambling behavior. The interviews were conducted by certified psychologists and took approximately 30 minutes. From our sample, 25 participants fulfilled at least three of the DSM-IV-TR criteria (American Psychiatric Association, 2000) for pathological gambling and therefore can be classified as problem gamblers (PG group, four females) (Fong et al., 2011; Weintraub et al., 2009). Furthermore, 23 participants were classified as habitual gamblers (HG group, three females). These participants fulfilled less than three criteria 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 non-gambling control group (C group, five females). 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 indicates 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 rank-sum test at  $p < .050$ . Given the fact that we compare extreme cases of behavior – participants with a medically diagnosed addiction to gambling vs. non-gambling 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 non-gambling 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 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 non-gambling 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) in order 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-Wilk test,  $W = 0.86$ ,  $p < .001$ ) and we have less than 30 observations per group (Moffatt, 2015), a (non-parametric) Kruskal-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). 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), 9 problem gamblers mainly engaged in non-strategic gambles (lottery, scratch cards or slot machines), 3 in strategic gambles (horse race

betting, sport betting or card games), and 13 in both types of gambles. From our HG group, 8 participants mainly engaged in non-strategic gambles, 9 in strategic gambles, and 6 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). 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 to 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:  $38.48 \pm 15.13$ ; Wejbera et al. (2017):  $33.32 \pm 11.55$ ) and gender distribution (our sample: 16% females; Wejbera et al. (2017): 11% females).

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 here. 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 here. The whole procedure took about 3.5 hours.

### **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 (i) gain and (ii) loss domains, (iii) probability weighting, and (iv) the degree of loss aversion. These four measures will be compared across the three groups and tested according to the above outlined theories on gambling behavior.

In the pure gain (loss) domain, one outcome is positive (negative) while 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, i.e., the point where the individual is just indifferent between the sure payment and the lottery. In the loss domain, this behavior is reversed, i.e., 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 2 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 under [http://www.ferdinandvieder.com/instructions\\_English\\_Euros.pdf](http://www.ferdinandvieder.com/instructions_English_Euros.pdf) and a summary of the used choice situations is available in Table S2. 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.

### **Non-parametric data analysis of risk preferences**

Based on procedures suggested by Vieider and colleagues (Vieider et al., in press; Vieider, Chmura, et al., 2015; Vieider, Lefebvre, et al., 2015; Vieider, Truong, Martinsson, & Khanh, 2013), we normalise 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 normalisation 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

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

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

$$CE(P) = w(p)x + (1 - w(p))y \quad (2)$$

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, i.e., 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 non-linear value function into our model would only pick up some of the attitudes towards 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 paper. 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  $\alpha = 0.5$  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

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

In the following, we will call  $(CE(P) - y)/(x - y)$  a normalised certainty equivalent. The normalised 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 paper will rely on normalised certainty equivalents instead of regular certainty equivalents. Since a higher regular certainty equivalent implies a higher normalised 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 gambles, 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 lotteries, 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 non-parametric 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 will use the

probability weighting function developed by Prelec (1998)

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

where  $\delta$  measures the elevation of the weighting function. Smaller values of  $\delta$  shift the weighting function upwards.  $\gamma$  measures the degree of curvature. Smaller values of  $\gamma$  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  $\delta$  and  $\gamma$  (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 seconds, 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 SI. 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 was analyzed using Ledalab ([www.ledalab.de](http://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 seconds after stimulus presentation (Boucsein, 1992), we

focus on the time interval of +1.5 to +9.7 seconds after revealing the shock probability. Due to 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 non-linear 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).

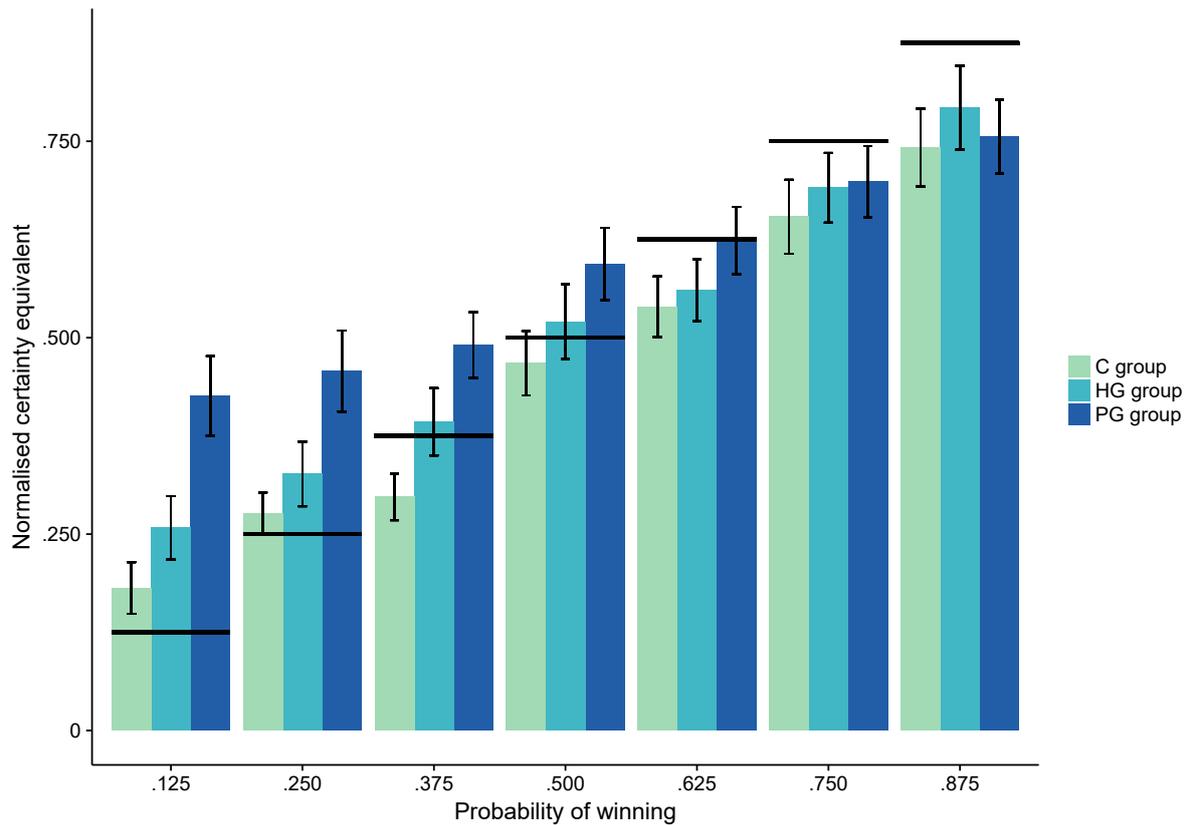
### Data availability

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

### Non-parametric results on behavioral risk preferences

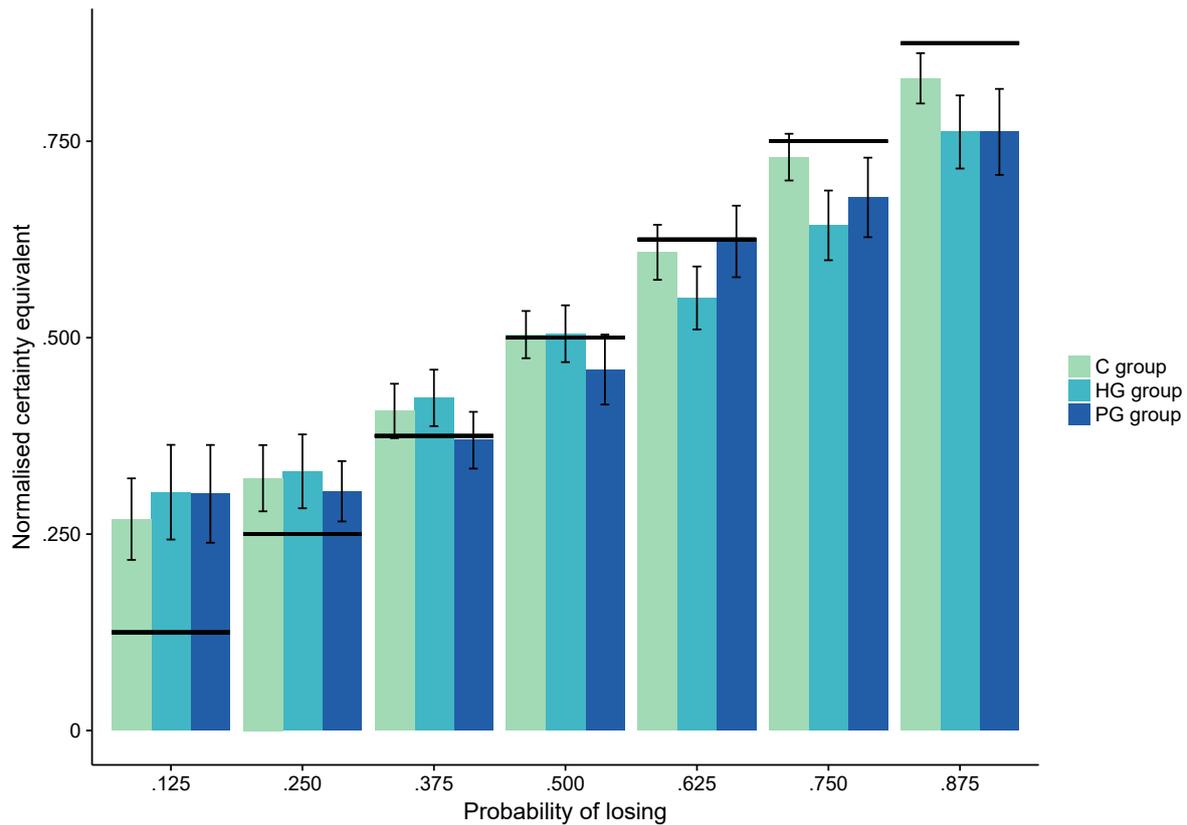
First, we compare the normalised certainty equivalents of the three different groups across decision domains. As outlined above, this analysis does not rely on prospect theory. We perform this analysis based on a group comparison as well as on SOGS-scores. Figure 1 shows normalised certainty equivalents by probability of winning for the three different groups. At the smallest probability of winning ( $prob = .125$ ), all three groups have a normalised certainty equivalent which is larger than the objective



*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 normalised certainty equivalent is above the black horizontal line, this indicates risk seeking. If the normalised certainty equivalent is below the black horizontal line, this indicates risk aversion.

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



*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 normalised certainty equivalent is above the black horizontal line, this indicates risk aversion. If the normalised certainty equivalent is below the black horizontal line, this indicates risk seeking.

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 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

Table 1

*Kruskall-Wallis tests and subsequent Post-Hoc tests after Dunn for different probability levels in the gain domain.*

Objective probability	p.overall	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	-	-	-

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 towards 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* towards changes in probability than the C group in the gain domain.

As a robustness check, we average the normalised certainty equivalents per participant and probability level, and compare all groups by means of Kruskal-Wallis tests (uncorrected for multiple testing) for each probability level. Our results show that the groups are significantly different at  $prob \leq 0.5$  with a significance level of  $p < .050$ . Exact p-values for the Kruskal-Wallis tests and p-values for subsequent Post-Hoc tests after Dunn are reported in Table 1.

In Table S4, we regress the normalised 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 towards changes in probabilities. In a nutshell, this analysis reveals that individuals with higher SOGS-scores are *more risk taking* and *less sensitive* towards 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 normalised certainty equivalents by probability of losing for the three different groups. The normalised 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, i.e., normalised certainty equivalents which 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 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 towards 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 non-significant 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

Table 2

*Kruskall-Wallis tests and subsequent Post-Hoc tests after Dunn for different probability levels in the loss domain.*

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

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 would be a component of gambling addiction, we would expect a more pronounced effect in the PG group, which we do not observe here.

As a robustness check, we average the normalised certainty equivalents per participant and probability level, and compare all groups by means of Kruskal-Wallis tests (uncorrected for multiple testing) for each probability level. We do not observe statistically significant differences ( $p > .200$ ). Exact p-values for the Kruskal-Wallis tests can be found in Table 2. As none of the Kruskal-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). While we observe a general pattern of probability insensitivity ( $\beta = 0.680$ ,  $SE = 0.025$ ,  $p < .001$ ), normalised 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 vs.

loss domain in the three groups, i.e., 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. Since 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 normalised 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 vs. loss domain in our three groups. These findings are replicated using SOGS-scores ( $\beta = 0.015$ ,  $SE = 0.002$ ,  $p < .001$ ) in Table S8.

Finally, we look at the normalised risk preferences for mixed prospects (see Figure S1). The average ratio of the potential loss to the potential gain 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 (non-parametric) Kruskal-Wallis test to identify 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, 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 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  $\delta$  and an average value of 0.67 (95% CI = [0.57, 0.77]) for  $\gamma$  (Fox & Poldrack, 2013). By looking at the 95% CIs, we see that the PG group has a smaller average value of  $\delta$  (mean = 0.63, 95% CI = [0.58, 0.69]) than the HG (mean = 0.86, 95% CI = [0.79, 0.93]) and C group. This indicates that the weighting function in the gain domain is shifted upwards. 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  $\gamma$  value is also smaller for the PG group (mean = 0.43, 95% CI = [0.32, 0.54]) than for the HG (mean = 0.65, 95% CI = [0.54, 0.77]) and C group which reflects a more pronounced inverse S-shape of the weighting function, i.e., 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 non-parametric analysis, we observe large overlaps of the CIs for both  $\delta$  and  $\gamma$  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.

### 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 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

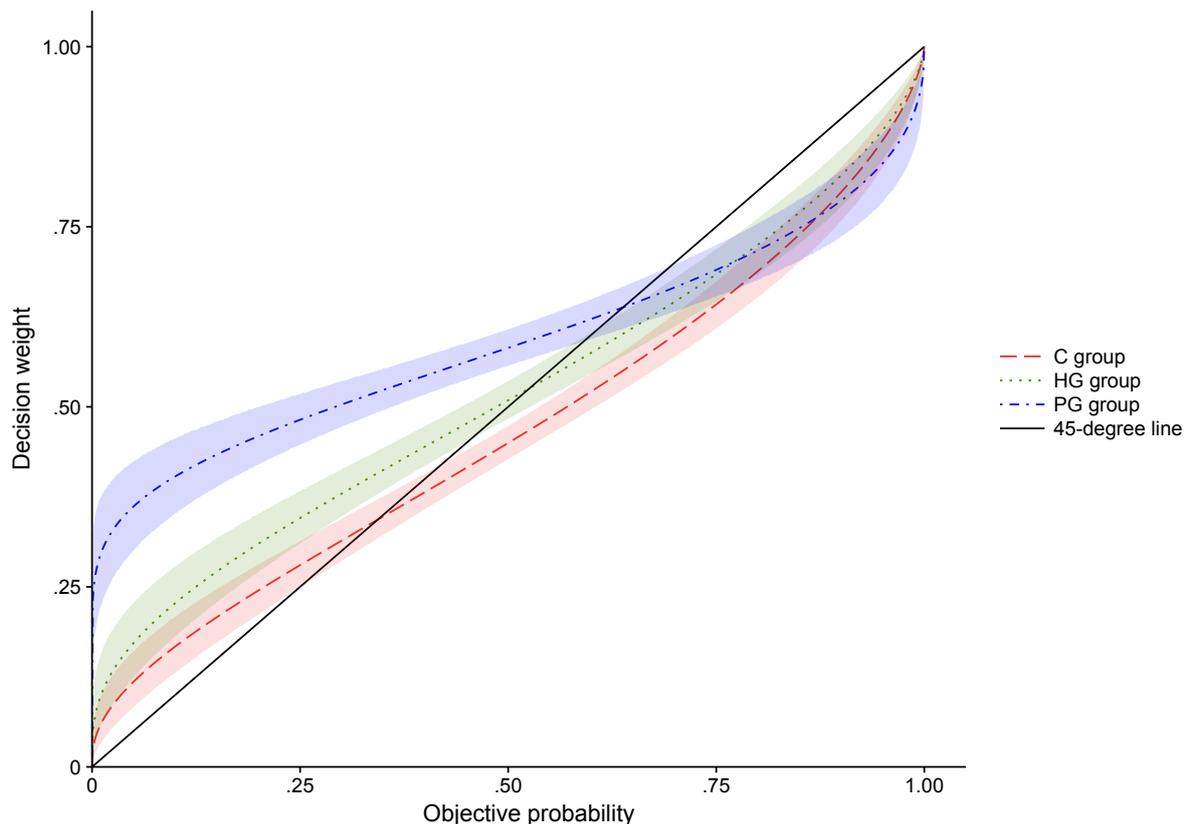
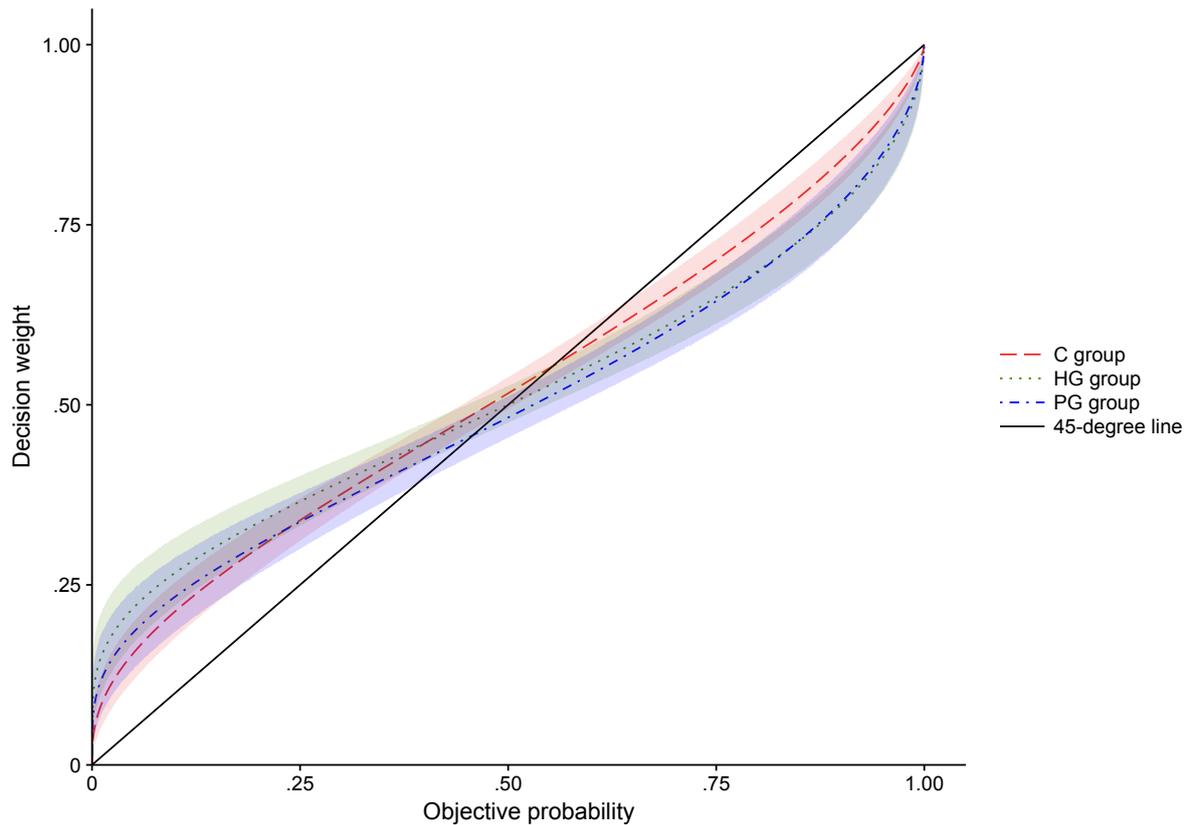


Figure 3. Fitted probability weighting functions by Prelec in the gain domain. Shaded areas indicate the 95% confidence intervals.

the different parametrization. The conclusions drawn from this analysis are in line with our approach and therefore are not reported here.

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  $\alpha = 0.5$  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 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  $\delta$  and  $\gamma$  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



*Figure 4.* Fitted probability weighting functions by Prelec in the loss domain. Shaded areas indicate the 95% confidence intervals.

domain. The 95% CIs of the estimates for the  $\alpha$  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 in the SI as Figures S4 to S7.

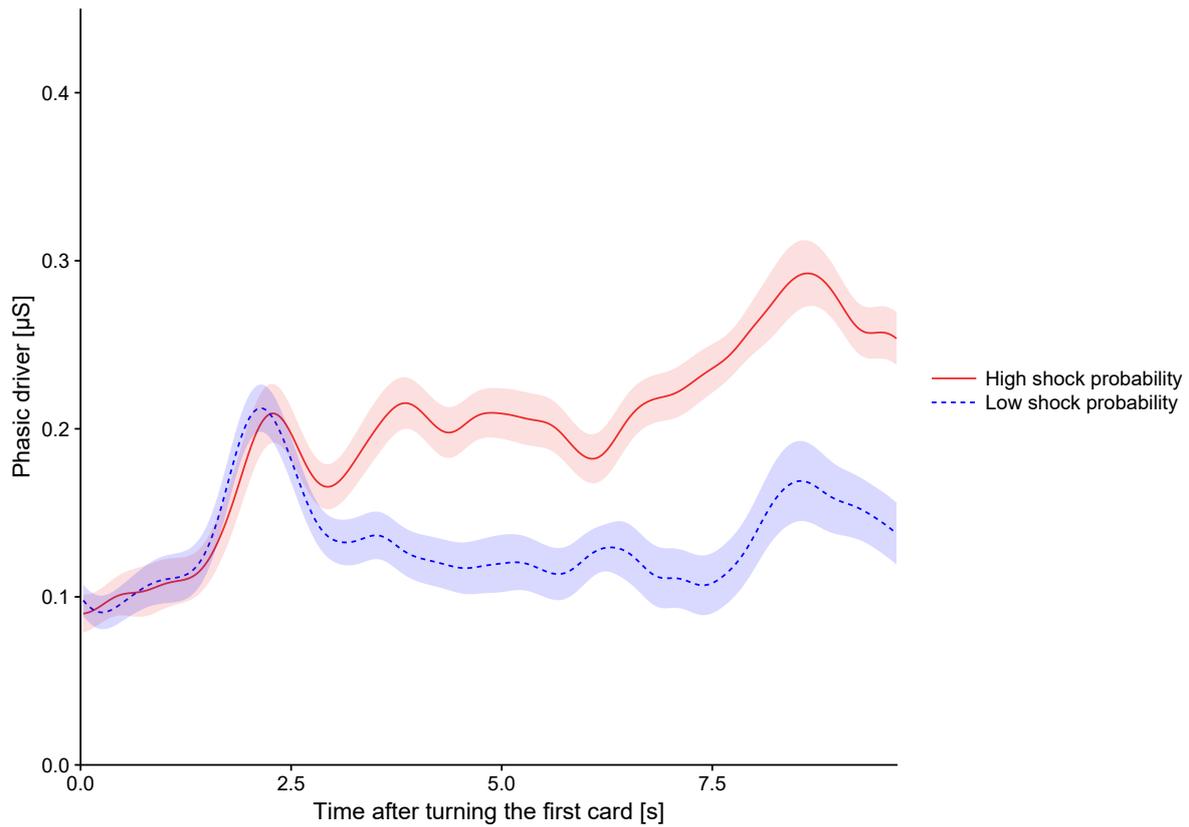
In a nutshell, our results remain stable, although admittedly the estimates became less precise which is indicated by larger confidence intervals. This finding, however, is not surprising because the value function will pick up some of the preferences for risk, which are otherwise taken up by the probability 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 ( $prob < .25$ : 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 SI 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.

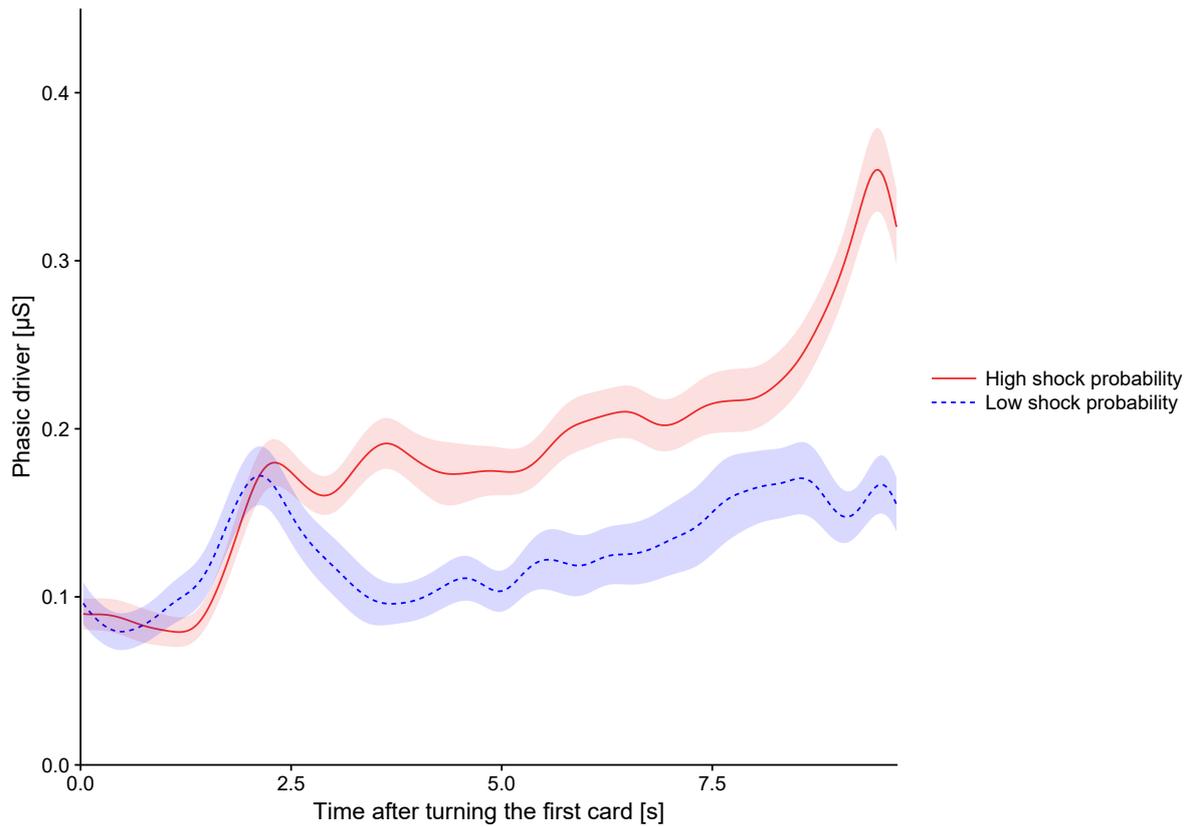
The statistical analysis of the data on the group level in Table S11 reveals that ISCRs increase with the probability of receiving an electric shock, which is indicated by a positive and significant coefficient for shock probability ( $\beta = 0.770$ ,  $SE = 0.060$ ,  $p < .001$ ). Additionally, ISCRs 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. The conclusions remain the same in the sense that there is no systematic relation between 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 non-significant.

Although the findings from our two tasks are based on different measures (physiological responses vs. choice behavior) and different stimuli (sensory stimulus vs.



*Figure 5.* Phasic driver by shock probability for the C group. Shaded areas indicate the standard errors of the mean.

monetary stimulus), they both point towards a similar degree of sensitivity towards losses. This 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). Since 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 towards negative outcomes for problem gamblers vs. controls.

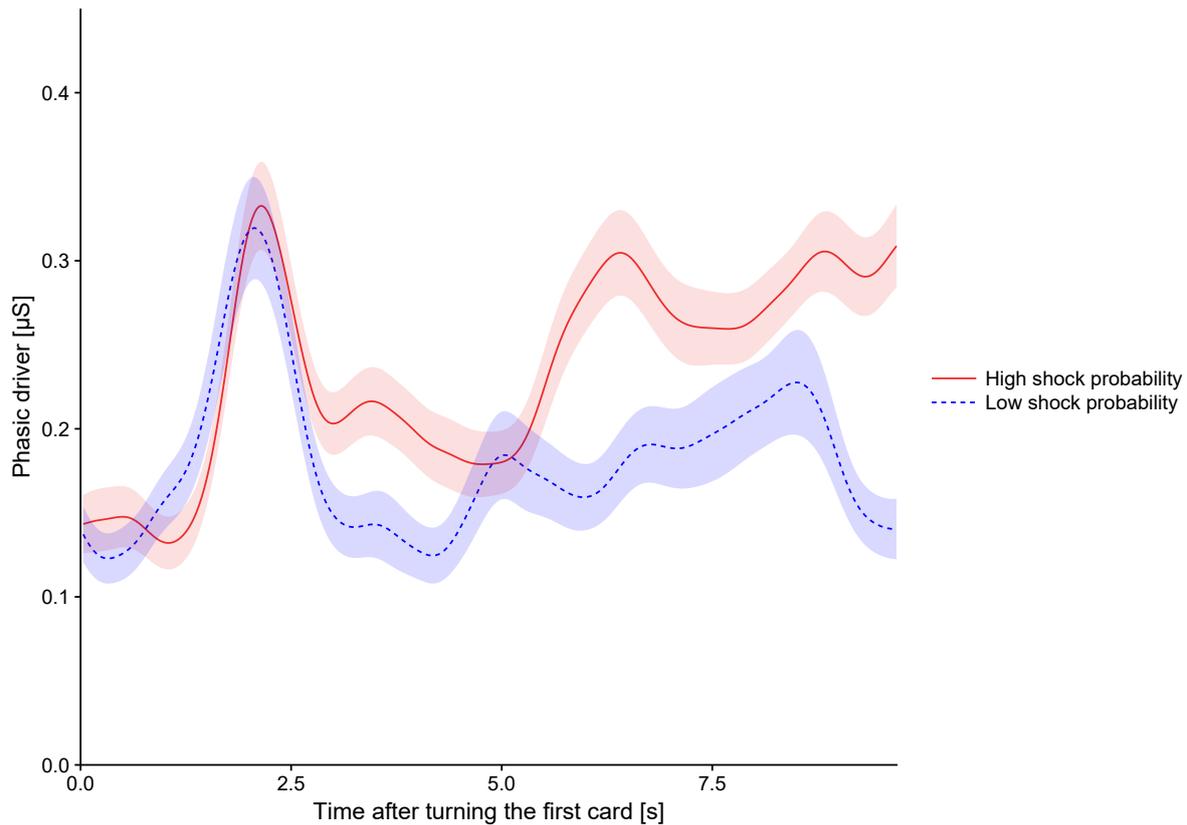


*Figure 6.* Phasic driver by shock probability for the PG group. Shaded areas indicate the standard errors of the mean.

## Discussion

Our data reveals that problem gamblers are systematically more risk taking and less sensitive towards changes in probabilities in the gain domain than non-gambling controls. This finding holds for a non-parametric 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 prospect 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 paper, we outlined three hypotheses which 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



*Figure 7.* Phasic driver by shock probability for the HG group. Shaded areas indicate the standard errors of the mean.

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 upwards (downwards), which makes gambling more attractive but also many other risky activities. Finally, the loss aversion hypothesis states that problem gamblers are less sensitive towards 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 upwards 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 upwards shift in the gain domain is neither amplified nor counterbalanced by changes in the loss domain. Our findings hold for a non-parametric group comparison, a non-parametric 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 fundamental 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. While 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). Secondly, 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). Thirdly, 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). While 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 non-gamblers at larger stakes exist. Therefore, additional research is required which involves significantly higher monetary outcomes and thereby more plausibly elicits participants' attitudes towards 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), while 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 to 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, due to ethical constraints, it is typically not possible that participants gamble with their own money in laboratory experiments. To study the loss domain it is therefore necessary to endow participants with money at the beginning of the experiment (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, i.e., 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. While some might prefer gambles with known probabilities, such as roulette, others might prefer gambles where probabilities are less clearly stated, such as horse betting. Due to 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 towards risk and/or ambiguity. Furthermore, we tried our best to match gamblers and non-gamblers in terms of variables that potentially affect risk preferences independent of gambling addiction. Due to 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. Based on 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 non-gambling 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 towards a similar degree of sensitivity towards 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. While 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.

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### **Author contributions**

U.S, T.v.E. and C.K. developed the study concept; all authors contributed to the study design; data collection was performed by C.C.P, L.N., S.W. and P.R.; P.R. performed the data analysis and drafted the manuscript under supervision of U.S. and C.F.C.; all authors provided critical revisions to the manuscript and approved its final version for submission.

### **Competing Interests**

The authors declare that they have no competing interests.