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Probability Distortion in the relationship between Depression and Problem Gambling: A Mediation Analysis

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Abstract

We posit that people with depressive symptoms are prone to problem gambling, and explore whether one possible driver of this is that depression increases misperception of probabilities. To test this hypothesis, we conducted a self-report survey on 230 regular gamblers recruited from Prolific. Depression was measured by the Major Depression Inventory (MDI), and problem gambling gambling was assessed by the South Oaks Gambling Screen: Revised for Adolescents (SOGS-RA). Perception of probabilities was elicited from 15 prospects with non-negative payoffs. Two central theoretical framework used in this study are mediation analysis and probability weighting function. Three main findings of the study are (i) probability distortion is not the mediator between depression and problem gambling, as there is no linear relationship between depression and probability distortion, (ii) in comparison to gamblers with no problem gambling, pathological gamblers overweight small probabilities more and underweight big probabilities to a lesser extent, and (iii) from an exploratory analysis, a depressive state has a quadratic effect on how individuals perceive big probabilities.

Keywords: problem gambling, depression, probability distortion, mediation, probability weighting function, prospect theory.

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All remaining errors are our own.

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1 Introduction

Problem gambling – an impulse to gamble continuously despite negative consequences or a desire to stop – has become a prevalent phenomenon worldwide, receiving as much attention as other addictive disorders such as substance abuse and dependence (Hofmarcher, Romild, Spångberg, & Håkansson, 2020). Calado and Griffiths (2016) estimate the range of problem gambling among adults across continents to be 0.1 to 3.4% in the period from 2000 to 2015. Particularly in Sweden, 1.3% of the population aged between 16 and 87 experienced gambling addictions, with an additional 2.9% experiencing less serious sub-clinical symptoms (Folkhälsomyndigheten, 2020). The hazard of problem gambling is not limited to the individual, but to the society as a whole. According to Hofmarcher et al. (2020), the societal costs[1] of this issue in Sweden in 2018 amounted to EUR 1.42bn, corresponding to 0.3% of the gross domestic product in Sweden, and was twice the tax revenue from gambling.

Moreover, from an economics perspective, exploring gambling behaviors can provide valuable insights on individual risk preference, as the two subjects have been suggested to be greatly correlated. A review paper from Stenstrom and Saad (2011) presents some recent neurogenetic evidence suggesting that high-testosterone individuals have a greater financial risk tolerance and therefore, are more likely to succumb to certain impulsivity-related pathologies such as gambling. Furthermore, in a study on problem gambling, Grall-Bronnec, Sauvaget, Samuel, and Boutin (2015) find significant clinical and structural similarities between addictive-like financial trading and gambling disorders, and support the notion of excessive trading as a subset of problem gambling. Additionally, Arthur, Williams, and Delfabbro (2016) study nearly 60 papers and books attempting to delineate the relationship between gambling, speculation, and investment. There is a reasonable consistency in the findings such that gamblers, speculators and investors have similar cognitive, personality and motivational attributes, with this relationship being particularly strong between gambling and speculation. Specifically, speculators who appear to be heavily involved in traditional forms of gambling tend to suffer with problematic speculation as well. For that, besides traditional gambling activities such as casino games, lotteries or sport betting, financial trading has been under scrutiny and it is proposed that excessive trading can be conceptualized as an unique subset of gambling disorders (Grall-Bronnec et al., 2015; Granero, Larrea, Fernández-Aranda, & Aymami, 2012). Interestingly, engagement in equity and

[1] This includes direct costs (e.g., health care and legal costs), indirect costs (e.g., lost productivity), and intangible costs (e.g., reduced quality of life due to gambling distress).

cryptocurrency markets by retail investors has increased by trading volume during the Covid-19 pandemic, and is likely used as means for gambling as traditional gambling avenues have been limited (Chiah & Zhong, 2020; Pinto-Gutierrez, 2021; Forsyth, 2020, May 22).

In this thesis, we are interested in the relationship between depression and problem gambling, as mental disorders have become a substantial economic burden globally (Rehm & Shield, 2019). We conduct a mediation analysis to explore if misperception of probabilities[2] is a driving force behind this relationship. We collect data from a self-reported survey on individuals who have engaged in gambling activities over the last six months. Several studies have indicated the role of depressive symptoms in the emergence, and/or the perpetuation of problem gambling, as gamblers may use gambling to release psychological tension and anxiety (Getty, Watson, & Frisch, 2000; Kessler et al., 2008). This phenomenon is further intensified as a consequence of Covid-19's lockdowns, social isolation and financial uncertainty (Pfefferbaum & North, 2020; Kumar & Nayar, 2020; Chiah & Zhong, 2020). Given this well-established correlation between depression and problem gambling, it is crucial to investigate the mechanisms driving this relationship, as they can provide grounds for effective treatments. Some commonly known mediating candidates include impulsivity and coping strategies (Clarke, 2006; Takamatsu, Martens, & Arterberry, 2015). Particularly, Clarke (2006) studies a sample of 159 New Zealand recreational student gamblers and finds that problem gambling symptoms increase with depression, and that one driving force behind this relationship is increased impulsivity. Takamatsu et al. (2015), in an experiment with 333 U.S. undergraduate gamblers, concludes that depressive symptoms have a significant indirect effect on gambling related problems via coping motivation and gambling refusal self-efficacy. In this study, we posit that misperception of probabilities is another potential driver, because of its close connections with depressive symptoms, as well as with gambling behaviors.

There is substantial evidence on how a depressive state negatively affects humans' cognitive ability, such as interpretation, attention, verbal and non-verbal learning, short-term and working memory, hence distracts patients' behaviors from rationality and affects their quality of decision-making (Leith & Baumeister, 1996; Pacini, Muir, & Epstein, 1998; Elliott et al., 1996; Lam, Kennedy, McIntryre, & Khullar, 2014). Misperception of probabilities is one of these consequences. According to Muris and van der Heiden (2006), children with depression and anxiety symptoms

[2] In this paper, the terms *misperception of probabilities* and *probability distortion* are used interchangeably.

overestimate the likelihood of future negative events, and underestimate that of positive events. Analogously, Strunk, Lopez, and DeRebeis (2016) suggest that individuals with high level of depression significantly exaggerate the occurrence of undesirable events. Moreover, using U.S. market price data, Kliger and Levy (2008) study the seasonal affective disorder and cloudiness on how investors distort probabilities. Given the close relationship between speculation and gambling (Arthur et al., 2016), we attempt to confirm this finding from Kliger and Levy (2008) using experimental data. As the existing literature is disperse in terms of samples and methods, more research is needed on the topic to provide a more consensus view on how perception of probabilities varies with depressive symptoms.

Perception of probabilities is crucially related to financial decisions such as gambling, investing, or purchasing insurance (Snowberg & Wolfers, 2010; Barseghyan, Molinari, O'Donoghue, & Teitelbaum, 2013). For example, Snowberg and Wolfers (2010) find evidence in favor of the view that misperception of probabilities drives the favorite–longshot bias – a phenomenon observed in gambling and financial markets. Specifically, speculators value long shots more than expected given how rarely they win, and value favorites too little given how often they win. Furthermore, gamblers' overestimation of their capacity to favourably control outcomes, and/or the likelihood of positive outcomes have been the main theme in highly-cited reviews (Crockford & el Guebaly, 1998; Goudriaan, Oosterlaan, de Beurs, & den Brink, 2004; Raylu & Oei, 2002; Toneatto, Blitz-Miller, Calderwood, Dragonetti, & Tsanos, 1997) and models (Blaszczynski & Nower, 2002; Sharpe, 2002) discussing gambling cognition. In this paper, we focus on how gamblers behave when facing probabilistic choices in the gain domain (non-negative prospects).[3] There are two pertinent studies that provide support on the topic of probability distortion in gamblers, nevertheless findings are not uniform. First, using several lotteries varying in probabilities and the prospect theory framework, Ligneul, Barbalat, Sescousse, and Domenech (2012) reveal an overall elevation in how pathological gamblers distort probabilities, relative to healthy gamblers. That is, individuals with gambling disorders overweight small probabilities and at the same time, underweight high probabilities to a lesser extent. However, evidence from Ring et al. (2018) only indicates a pronounced overestimation of small probabilities from pathological gamblers, compared to participants in the control group. Subjects in both of the groups behaved similarly with respect to prospects with high winning chances. As the sample sizes in these two studies

[3] A study investigating both the gain and the loss domain will provide a more comprehensive view of the topic, but within the scope of this master's thesis, we consider this approach to be the most feasible.

are comparatively small according to scientific standards (38 and 74 participants, respectively), they may be prone to an increased risk of false positive, or false negative results (Button et al., 2013). We hope to refine the estimates by adopting a larger sample size.

The paper consists of five main sections. Next, we introduce two central theoretical frameworks used in this study: mediation analysis and probability weighting function. In section three, we present the study method, including how data is collected and analysed. Results are presented in section four, followed by a discussion and concluding remarks in section five.

2 Theoretical framework

2.1 Mediation analysis

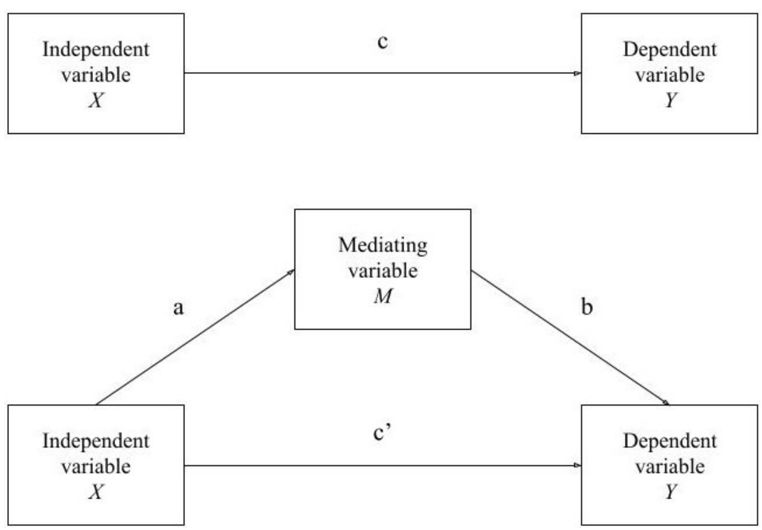
We adopt the basic mediation framework put forward by Baron and Kenny (1986), which is the most cited article for mediation analysis (Google Scholar, 2021), and has previously been used to explore the mediation mechanism in areas related to our research topic.[4] We follow previous literature despite the Baron and Kenny (1986) framework's lower statistical power according to MacKinnon, Lockwood, Hoffman, West, and Sheets (2002). In this study, the authors study 14 different tests for mediation analysis and present other frameworks with higher power compared to Baron and Kenny (1986), such as Bollen and Stine (1990); Efron (1979, 1987).

Figure 1 visualizes how we apply the Baron and Kenny (1986) framework to our study. Depression is the independent variable; Problem Gambling (PG) is the dependent variable and Probability Distortion (PD) is the presumed mediator. In general, PD is said to exert a mediating function when it accounts for the relation between Depression and PG. The model assumes a three-variable system where there are two paths leading to PG: (i) the direct path from Depression (path c) and (ii) the indirect path where the impact of Depression goes through PD (path a and b). The goal of the mediation analysis is to calculate the indirect effect ($ab = c - c'$) and test if this effect is statistically different from zero. There are a number of tests that have been proposed to achieve this, notably the Sobel test (Sobel, 1982) and bootstrapping (Bollen & Stine, 1990; Shrout & Bolger, 2002).

[4] See, e.g., Clarke (2006); Takamatsu et al. (2015); Mansueto et al. (2015) for the application in depression and gambling; Civelek, Uca, and Çemberci (2015); d'Aleo and Sergi (2017); Omokri and Nwajei (2018) for the application in economic growth.

The framework relies on three fundamental assumptions such that the mediation model is identified if these assumptions are fulfilled. The first assumption is no reverse causality, that is, PG does not cause PD nor Depression. Second, the main variables, especially the mediator are assumed to be measured with very high reliability. If PD suffers from measurement errors, the effect of PD on the PG (path b) is likely to be underestimated and the effect of Depression on PG (path c') is likely to be overestimated if ab is positive. Measurement error in Depression attenuates the estimate of path a and c. Measurement error in PG does not bias unstandardized estimates, but it does bias standardized estimates. Third, there is no omitted variable bias. In other words, there is no other factor that affects both PD and PG that researchers fail to control for. Furthermore, if the mediation analysis is conducted by a general linear model, it also makes the corresponding standard assumptions (i.e., linearity, homogeneity of error variance, and independence of errors). According to MacKinnon, Fairchild, and Fritz (2007), it may be difficult, and sometimes impossible to test these assumptions in most cases, so a more realistic approach is to tentatively motivate the mediation by findings from prior research, such as randomized controlled trials. We acknowledge that the most important assumptions, no reverse causality, no measurement error and omitted variable bias are not fully held, and we address them in detail in the discussion section.

Figure 1: Mediation model



In this study, we want to empirically investigate the relationship between depression and problem gambling via the mediation path of probabilities misperception. We follow the four steps detailed in Baron and Kenny (1986): first, we show a correlation between depression and problem gambling by regressing the former on the latter. This step establishes a relationship that may be mediated. Second, we show that depression is a predictor for misperception of probabilities. Third, we examine if misperception of probabilities affects problem gambling by running a regression with problem gambling being the dependent variable and depression and misperception of probabilities as predictors. Finally, to confirm the mediation role of misperception of probabilities in the depression – problem gambling relationship, the effect of depression on problem gambling controlling for misperception of probabilities (path c') should be zero (completely mediated) or be reduced significantly (partially mediated). The effects in steps three and four are estimated in the same equation. If these relationships are confirmed, we would test whether the indirect effect is statistically different from zero. We do so with the highly recommended bootstrapping method (Bollen & Stine, 1990; Shrout & Bolger, 2002).[5]

2.2 Misperception of probabilities

2.2.1 Probability weighting function

It is generally accepted that the expected utility (EU) model of choice and linear probabilities perception are incommensurate with empirical and experimental evidence. Most alternatives to the EU, notably prospect theory by Kahneman and Tversky (1979) and rank-dependent utility by Quiggin (1981, 1982) relax the second feature, i.e., linearity in probabilities. In 1992, Tversky and Kahneman introduced the cumulative prospect theory, which was an improvement from the original theory by incorporating the reference point concept and the rank-dependent framework to the cumulative probability distribution function. This work is among the most prominent studies contributing to the understanding of how individuals perceive probabilities and behave under risks and uncertainties. Tversky and Kahneman (1992) presented experimental evidence that individuals overweight small probabilities and underweight medium to high probabilities, thus confirming the fourfold pattern of risk attitudes: risk aversion in gains and risk-seeking in losses of high probability, risk-seeking in gains and risk aversion in losses of low probability.

[5] Bootstrapping is a non-parametric method that uses repeated random sampling with replacement. From each of these samples the indirect effect is computed and a sampling distribution can be empirically generated. From the distribution, confidence interval, p-value or standard error can be determined. If zero is not in the confidence interval, then it can be concluded that the indirect effect is statistically significant. Previously, the Sobel test (Sobel, 1982) was the most commonly used test, however, the bootstrapping method (along with others) has been proposed as an efficient replacement for the conservative and low-power Sobel test (MacKinnon et al., 2002).

One of the key elements in Kahneman and Tversky's Cumulative Prospect Theory (CPT) is the probability weighting function – a non-linear function that transforms objective probabilities (p) into "decision weights": $p \to w(p)$. From the pioneer work of Kahneman and Tversky, many functional forms have been suggested (Goldstein & Einhorn, 1987; Tversky & Kahneman, 1992; Luce, Mellers, & Chang, 1993; Wu & Gonzalez, 1996; Prelec, 1998). Empirical estimates exhibit three prominent properties of weighting functions: $w(0) = 0$ and $w(1) = 1$, "regressive" (overweighting (underweighting) small (large) probabilities), and inverted S-shaped (first concave then convex, implying high sensitivity toward the end points of the probability distribution) (Camerer & Ho, 1994; Tversky & Kahneman, 1992; Tversky & Fox, 1995; Wu & Gonzalez, 1996).

A number of studies have fitted different weighting functions to experimental data and assessed their explanatory power. In general, whilst a one-parameter function is adequate for aggregate population data, two-parameter models outperform one-parameter models when fitting individual preferences (Gonzalez & Wu, 1999; Bleichrodt & Pinto, 2000; Sneddon & Luce, 2001; Stott, 2006; Takemura & Murakami, 2016). As we fit the weighting function to individual data, we use the Prelec two-parameter functional form (Prelec, 1998) for all the analyses in this study, as recommended by previous studies. This weighting function has also been extensively used in neuroeconomics and behavioral sciences, thanks to its desirable merits: consistency with much empirical evidence, axiomatic proof, and parsimony (Al-Nowaihi & Dhami, 2010).

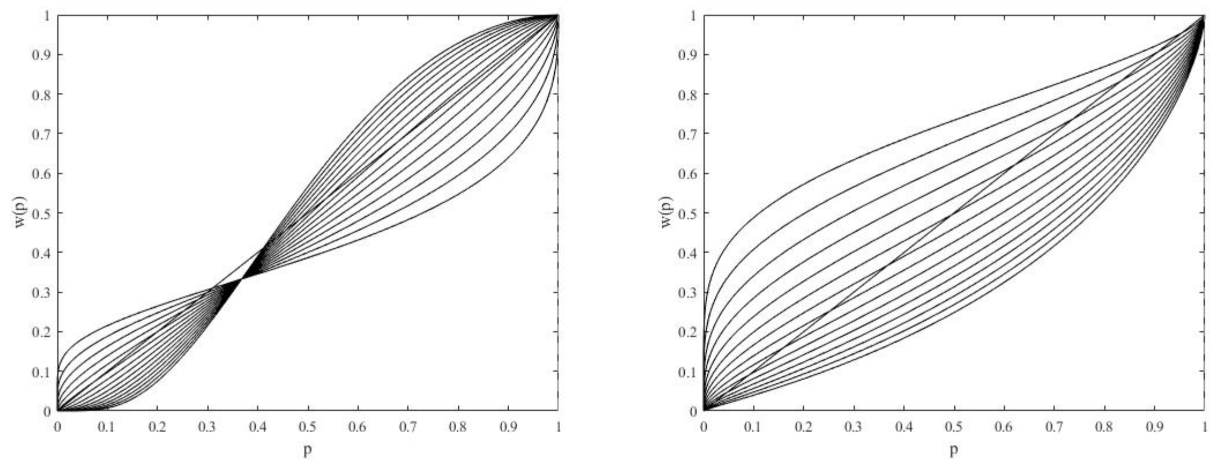
2.2.2 Prelec two-parameter functional form

The functional form of the probability weighting function used in this study is as follows:

$$w(p) = exp(-\delta(-ln(p))^{\alpha}), \tag{1}$$

where $w(p)$ is the weighted (predicted) probability, and p is the objective probability. δ and α are the estimated parameters. While δ indicates the elevation of the weighting function, α measures the degree of curvature. Higher values of δ shift the function downward, and smaller values of α correspond to the more pronounced inverse S-shape. Beside the fixed points at $p = 0$ and $p = 1$, when $\alpha \neq 1$, there exists a unique inflection point, $\tilde{p} \in (0; 1)$, at which $w''(\tilde{p}) = 0$. At this point, the individual switches from overweighting (underweighting) to underweighting (overweighting) probabilities. For the illustration of how the weighting function changes with respect to the parameters, see Figure 2.

Figure 2: Prelec two-parameter weighting function with varying parameters



Note: The left panel fixes δ at 1.1 and varies α from 0.4 to 1.8. The right panel fixes α at 0.7 and varies δ from 0.4 to 1.8. α primarily controls curvature and δ primarily controls elevation.

To provide an intuitive understanding of the weighting function, Gonzalez and Wu (1999) review psychological interpretations of δ and α, such that one can think of δ (elevation) as the attractiveness of a gamble, and α (curvature) as probability discriminability. Logically, elevation and curvature are independent. Discriminability can be illustrated through two extreme cases (see the left panel, Figure 2); the most upper function (α close to zero) approaches the step function and the one that is almost linear (α close to one). The step function indicates less sensitivity to changes in probabilities between zero and one, corresponding to when an individual looks at probability zero as "certainly not", probability one as "certainly", and all probabilities in between are treated equally as "maybe". Attractiveness, concerning the degree of over/under weighting (the change in δ – see the right panel, Figure 2), can be interpreted as how an individual compares different probabilities-related activities: for example he/she finds one type of gambling more attractive than the others if $w_1(p) > w_2(p)$ for all $p \in (0; 1)$. Numerically, this also means w_1 has a smaller value of δ (holding α constant) than w_2.

3 Method

3.1 Data collection

Data was collected through an anonymous online survey. All participants were recruited through Prolific (www.prolific.co) and took part in the study from March 6 to March 20, 2021. Eligible participants were at least 18 years old, had at least 150 previous submissions and an approval rating of minimum 95% on the Prolific platform. The study further included participants who have engaged in at least one gambling activity (either online or offline) in the last six months.[6] Average time to complete the study was 15 minutes. The full survey is reported in Appendix A.

Each participant was paid £2.30 for completion of the survey. Following Ariely and Norton (2007), to make our survey more comparable to the real world setting, we paid out one randomly chosen prospect to one of the participants.

The measures we use elicit behaviors or emotional states over various periods. In order to obtain measures that are corresponding, we altered the time period based on which the measure was elicited. If so, this is explained and discussed when the measures are introduced.

3.2 Procedure

3.2.1 Participation

The experiment was implemented using Qualtrics (`www.qualtrics.com`). Before participating, respondents were fully informed that information on decision-making, mental health, and gambling behavior was collected, that participation was voluntary, and that withdrawal from the study would not in any way impact future involvement in services for Prolific. Responses were anonymous and kept strictly confidential, and no party could identify a participant based on his/her answers, or if an individual has participated in the study. Further, IP address collection was disabled. Each participant has a unique Prolific code. No personal information can be retrieved from this code, and Prolific has no access to the data collected (Moodie, 2018).

3.2.2 Prospects

To measure misperception of probabilities, we used 15 hypothetical decision tasks (prospects) from Tversky and Kahneman (1992).[7] Following Millroth, Juslin, and Nilsson (2019), to control for the possibility of results being driven by a specific presentation order, four sets of prospect

[6]The screening question was simply "In the last six months, have you regularly engaged in any gambling activities – either online or offline?" with no suggestions or examples on types of gambling activities included to avoid self-selection bias.

[7]Only prospects that offer a non-negative payoff or zero otherwise are selected.

series with randomized presentation order were created within the survey.[8]

Participants were randomly assigned to one of the prospect sets by Qualtrics. The task asked participants to repeatedly indicate their preference between a descending series of sure outcomes (logarithmically spaced between the extreme outcomes) and a risky gamble. The format is illustrated in Table 1 for a prospect with 5% chance of receiving $100 and a 95% chance of receiving nothing, with the following amounts as sure payment. For this prospect, participants are asked to indicate their preference between sure payments of $100, $56.2, $31.6, $17.8, $10.0, $5.6, $3.2, $1.8, and $0, or the risky gamble. Participants that indicate their preference for the sure payment at $5.6 but prefer the risky gamble at $3.2 would place their check marks as follows.[9]

Table 1: Example of a prospect

	Prefer sure payment	Prefer gamble
$100 for sure	•	
$56.2 for sure	•	
$31.6 for sure	•	
$17.8 for sure	•	
$10.0 for sure	•	
$5.6 for sure	•	
$3.2 for sure		•
$1.8 for sure		○
$0 for sure		○

To obtain a more refined estimate of the certainty equivalent value of the prospect, a second series of sure outcomes, linearly spaced between the lowest sure amount accepted and the highest sure amount rejected, is displayed after the first series, in the above example between $5.6 and $3.2. The final measure of the certainty equivalent of the prospect for each participant is the midpoint between the lowest sure amount accepted and the highest sure amount rejected in the

[8] Presentation order of the prospects for Set A: 9, 13, 10, 15, 6, 12, 2, 5, 8, 14, 7, 11, 3, 1, 4. Presentation order for Set B: 8, 11, 6, 13, 2, 5, 10, 15, 4, 1, 3, 12, 9, 14, 7. Presentation order for Set C: 3, 5, 15, 8, 1, 9, 13, 14, 10, 6, 11, 2, 4, 12, 7. Presentation order for Set D: 11, 12, 2, 9, 7, 3, 8, 4, 1, 14, 6, 5, 10, 13, 15.

[9] Following previous studies on risk preferences, participants who indicate their preference for the sure payment at $5.6 but a risky gamble at $3.2, would prefer the risky gamble at $1.8 and $0 as well (Tversky & Kahneman, 1992; Gonzalez & Wu, 1999; Vieider et al., 2015).

second series of sure outcomes. Note that participants did not generate a certainty equivalent from the elicitation procedure. Rather, this value is determined from a menu of options presented to the participant. This two-step procedure is conventionally used in studies on risk preferences (Tversky & Kahneman, 1992; Tversky & Fox, 1995; Gonzalez & Wu, 1999). The procedure is used to obtain refined estimates when prospect payoffs vary greatly in size. Studies deviating from this procedure have used either one long series of sure outcomes or asked participants directly to fill in the lowest sure amount accepted, however, results remain similar (Ring et al., 2018; Rieger, Hens, & Wang, 2015; Millroth & Juslin, 2015).

3.2.3 Numeracy

Numeracy and risk literacy was measured using the single-item format Berlin Numeracy Test (Cokely, Galesic, Schulz, Ghazal, & Garcia-Retamero, 2012). The test was reduced to single-item format (from four items) due to budget constraints. As the intercorrelation between the single-item test and the four-item test is high at 0.75, statistically significant at 1% level (Cokely et al., 2012), it is safe to assume that the impact caused by this reduction is marginal. While other tests on numeracy exist, the Berlin Numeracy Test has been the most widely used for its high predictive power and has been validated across diverse samples (Cokely et al., 1998; Lindskog, Juslin, Kerimi, & Winman, 2014; Millroth & Juslin, 2015). To prevent participants from looking up the answer online, we changed the wording and numbers used in the test, however, the logic and the deduction remain the same.

3.2.4 Depression

The Major Depression Inventory (MDI) was used to measure depression of participants by self-reported symptoms. The MDI is widely used in practice and in research to screen for symptoms of depressive illness (Bech, Timmerby, Lunde, & Soendergaard, 2015; Nielsen, Ørnbøl, Bech, Vestergaard, & Christensen, 2017). The test consists of 12 questions on mental health symptoms. Each question is scored between 0 (at no time) and 5 (all the time). For questions 8-9 and 11-12, as they cover the same symptom categories, only the highest response score is used in the total MDI score (Bech, Rasmussen, Olsen, Noerholm, & Abildgaard, 2001). In total, the questionnaire produces an absolute measure of depression representing a severity rating score of 0-50. We divide participants into three groups following Olsen, Jensen, and Noerholm

(2003): no depression between 0-20; mild to moderate depression between 21-29[10]; and severe depression between 30-50. The MDI is extended to six months from two weeks to correspond to the time frame of problem gambling behavior. This is likely to overestimate the depression status of respondents, however, as we mainly focus on the relative scale of depression, we do not see this as a too serious issue.

3.2.5 Problem gambling

A measure for problem gambling was obtained from the South Oaks Gambling Screen: Revised for Adolescents (SOGS-RA) score, originally developed by Winters and Stinchfield (1993). The SOGS-RA was chosen for its internal consistency and reliability in identifying problematic gambling behavior (Poulin, 2002). The questionnaire consists of 12 questions and examines distinct symptoms of problem gambling of participants over the last 12 months. In order to capture the same time period as assessed in our measure of depression symptoms, we shorten the time frame to six months. As each question is answered with a binary *Yes* or *No*, questions are scored either 0 (non affirmative) and 1 (affirmative), producing a final score of 0-12. Participants are categorized into three groups: no problem gambling is determined for scores between 0-1; at risk of problem gambling between 2-3; and pathological gambling between 4-12 (Poulin, 2002).

3.2.6 Covariates

Finally, a set of demographic questions is included in the survey. We collected data on gender, age, level of education, income, and marital status. To gain a better understanding of gambling behaviors, participants were asked about the types of gambling activities they engaged in, and the reasons why they took part in those activities.

3.3 Modelling probability distortion

3.3.1 Scaling

According to Cumulative Prospect Theory, the subjective utility of the prospect that offers $\$x$ with probability p_i is given by:

$$V(x, p_i) = w(p_i)v(x),$$

[10]Mild depression (scores between 21-24) and moderate depression (scores between 25-29) are combined to simplify the analysis.

where $v(x)$ is the value function, and $w(p_i)$ is the subjective probability transformed by the weighting function. Based on the certainty equivalent approach by Tversky and Kahneman (1992), we have:

$$c = w(p_i)v(x) \Rightarrow w(p_i) = \frac{c}{v(x)},$$

where c is the certainty equivalent. For simplicity, we assume a linear value function, that is, $v(x) = x$ (Ring et al., 2018; Ligneul et al., 2012). Then, the ratio c/x is the perceived probability $w(p_i)$ associated with each prospect. For example, a participant who requires a certainty equivalent of \$40 for a prospect that offers $p_i = 0.25$ of winning \$100 behaved as if the winning chance of this gamble was $w(p_i) = \frac{40}{100} = 0.40$.

In the second step, $w(p_i)$ and p_i from the 15 prospects are fitted using the functional form by Prelec (1998) in equation (1). This procedure takes repeated probabilities in some prospects into account[11], and therefore can further separate noise from underlying preferences (Vieider et al., 2015). The non-linear least square regression is performed by the command *nl* in STATA, with initial value of 0.7 for both α and δ (Ring et al., 2018). In the end, each participant will have unique values for α and δ, such that the total sum of squares is minimized.

3.3.2 Calculation of probability distortion

As far as we know, no studies have taken the probability weighting function into the relationship with other variables, such as running regressions using predicted values from the weighting function. Therefore, we could not find any reference on how we can integrate distorted probabilities to the regressions. A natural way is to use the estimated parameters as variables, however, it makes the analyses cumbersome as there are two parameters in the weighting function we use, and it is abstract to interpret and visualize the effects. Nevertheless, we propose that the definite integrals of the weighting function and the identity line can be used as an alternative. First, definite integrals allow us to look at a range of probabilities (e.g., 0 to 25%, 75 to 100%) or the entire probability distribution (0 to 100%) for a general level of individual probability distortion, which is more interesting and intuitive than just looking at one specific probability (e.g., 1%, 10%, 99%). Second, this method incorporates both parameters (δ and α) into the analysis, thus simplifying the regression procedure. Third, the integrals can be understood as the area created by the weighting function and the identity line, which is also the degree to which

[11] 0.01, 0.10, 0.90, 0.99 were repeated in two prospects, and 0.50 was repeated in three prospects.

an individual deviates from the objective probabilities, hence facilitates result interpretations. Last but not least, it is exciting to apply this basic and familiar calculus concept to the thesis. Nonetheless, one limitation of this method is that the probability weighting function does not guarantee an accurate measure of all individuals' probabilities perception, as it does not take into account stochastic factors affecting the respondents while doing the prospect tasks like attention, mood, or adverse behaviors. For example, for one individual, the function can explain a high proportion of variance in their behavior, whilst for the other, the predicted perceived probabilities may be far from the observed perceived probabilities. To account for this shortcoming, in the robustness test, we provide a secondary measurement of probability distortion which is only based on observed perceived probabilities.

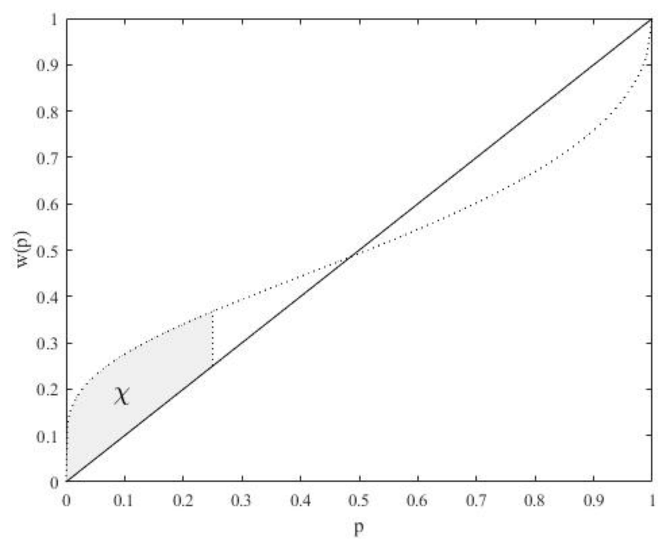
The method to obtain probability distortion is as follows. As previously mentioned, each participant has a unique probability weighting function characterised by different values of δ and α. To elicit how much an individual's perception of probabilities deviates from the objective probabilities, we calculate the integrals of the difference between the fitted weighting function and the identity line. The integral will be positive if the fitted curve is above the line, i.e., probability overweighting, and negative if the curve is below the line, i.e., probability underweighting. The absolute value of the integral is the area formed by the curve and the line. The larger the area, the more distorted the perceived probability interval predicted by the weighting function is. Equation (2) elucidates the integral formula,

$$\begin{aligned} \chi &= \int_{p_0}^{p_1} (w(p) - p)dp \\ &= \int_{p_0}^{p_1} (exp(-\delta(-ln(p))^{\alpha}) - p)dp, \end{aligned} \tag{2}$$

where χ is the area formed by the curve (weighting function) and the identity line (where $w(p) = p$). The weighting function, $w(p)$, is the two-parameter functional form by Prelec (1998). The interval of interest is defined by p_0 and p_1. Figure 3 illustrates the corresponding integral from $p_0 = 0$ to $p_1 = 0.25$.

Having illustrated how we measure probability distortion, we now turn to the description of the variables. As previous studies on the weighting function have pointed out the insensitivity of individuals toward the change in intermediate probabilities (Tversky & Fox, 1995; Tversky & Wakker, 1995; Stott, 2006), in this paper, we are interested in the perception of small probabilities and big probabilities. First, we construct the low probability distortion variable (LPD), which is the integral of the interval from 0 to 25%. Second, we construct the high probability distortion variable (HPD). For this, we investigate the interval from 75 to 100%. These intervals are arbitrarily selected. To make sure the results are not impacted by the choice of specific intervals, we would repeat the regression with other intervals (0 to 5% and 0 to 10% for LPD, 90 to 100% and 95 to 100% for HPD). After obtaining the integrals, we multiply the variables by 100 to simplify interpretation.

Figure 3: Integral calculated from the weighting function



Note: The horizontal line is the identity line where $w(p) = p$. The weighting function is estimated with $\alpha = 0.5$, $\delta = 0.85$. The shaded area indicate the integral of $(w(p) - p)$ from $p_0 = 0$ to $p_1 = 0.25$.

3.4 Mediation model

3.4.1 Main analysis

Table 2 summarizes the main variables used in the OLS regressions for the mediation analysis.

Table 2: Main variables summary

Measurement	Variable	Type	Description
Probability distortion	LPD	continuous	Low probability distortion, from 0 to 25%. Range: -3.125 to 21.875
	HPD	continuous	High probability distortion, from 75 to 100%. Range: -21.875 to 3.125
Depression	*depression*	discrete	MDI total score. Range: 0 to 50.
Problem gambling	PG	discrete	SOGS-RA total score. Range: 0 to 12.
Covariates (C)	*age*	discrete	Age of the participant (years).
	female	binary	= 1 if female, = 0 if male.
	employed	binary	= 1 if employed, = 0 if student, unemployed or retired.
	education	categorical	High school or less, College or bachelor, Postgraduate or professional degree.
	single	binary	= 1 if single, = 0 if cohabiting or married.
	income	ordinal	Gross annual income: less than USD 10,000 (0) to more than USD 150,000 (11).

To simultaneously explore the mediating effect of small probabilities and big probabilities distortion on the depression and problem gambling relationship, we conduct a multiple mediation analysis based on Takamatsu et al. (2015). Traditionally, the mediation model is identified by estimating a series of multiple regression equations. We conduct the multiple mediation analysis using the SEM (Structural Equation Modeling) program in Stata with bootstrapped standard errors and confidence intervals from 599 replications (Wilcox, 2010). This section describes in detail our three hypotheses in accordance to the mediation analysis by Baron and Kenny (1986) outlined in the theoretical framework, and how the indirect (mediation) effect is calculated and tested for significance. All analyses are two-tailed tests at 5% significance level.

Primary hypotheses:

Hypothesis 1: There is a significant correlation between depression and problem gambling.

$$PG_i = \beta_0 + \beta_1 \times depression_i + \beta_2 \times C_i + \varepsilon_i \tag{3}$$

Hypothesis 2: The relationship between depression and problem gambling is mediated by misperception of probabilities, that is, the effect of *depression* on PG becomes smaller in magnitude when LPD and HPD are included in the regression. Simultaneously, the effects of LPD and HPD on PG are significant.

$$PG_i = \beta_0 + \beta_1 \times depression_i + \beta_2 \times LPD_i + \beta_3 \times HPD_i + \beta_4 \times C_i + \varepsilon_i \tag{4}$$

Secondary hypotheses:

Hypothesis 3: There is a significant correlation between depression and probability distortion.

$$LPD_i = \beta_0 + \beta_1 \times depression_i + \beta_2 \times C_i + \varepsilon_i \tag{5}$$

$$HPD_i = \beta_0 + \beta_1 \times depression_i + \beta_2 \times C_i + \varepsilon_i \tag{6}$$

If the three hypotheses hold, we continue with estimating the mediation (indirect) effect, which equals the difference between the total effect (β_1 from equation (3)) and the direct effect (β_1 from equation (4)). Finally, we use the bootstrapping method to determine the confidence interval of the sampling distribution of the indirect effect and test if this effect is significant.

3.4.2 Robustness test

For robustness test, we construct a secondary measure for probability distortion based on the perceived probabilities (c/x) obtained from the 15 prospects. That is, the distortion for one specific probability equals the square of the difference between perceived probabilities and stated probabilities. Note that for probabilities that appear more than twice (0.01, 0.1, 0.9, 0.99 in two prospects, 0.5 in three prospects), the average perceived probability is used. The method is shown in equation (7),

$$PD_i = [(c/x)_i - i]^2, \tag{7}$$

where $i \in \{0.01, 0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95, 0.99\}$.[12] Once again, we would focus on low probabilities distortion (LPD) and high probabilities distortion (HPD). LPD consists of all distortion estimates for 0.01, 0.05, 0.10, and 0.25. HPD is the sum of the distortion estimates for 0.75, 0.90, 0.95, and 0.99.

4 Results

4.1 Preliminary analysis

Descriptive statistics are provided in Table 3. We report data on 230 participants (159 men, 70 women, 1 other) with age ranging from 19 to 64 (M = 36.03, SD = 11.02). Participants are mostly from Europe (United Kingdom, Portugal, Poland) and North America (United States,

[12] For example, if a person perceives 0.10 as 0.15, his/her distortion for 0.10: $PD_{0.1} = (0.15 - 0.1)^2 = 0.0025$.

Canada). The majority of the sample (85.7%) has attended college or university. There is no systematic difference with respect to problem gambling, depression and probability distortion between prospect sets (see Table B1, Appendix B). Our sample appears similar to those in Ring et al. (2018) and Wejbera, Müller, Becker, and Beutel (2017) in terms of age and gender distribution.[13]

Table 3: Descriptive statistics ($n = 230$)

Characteristics	M	SD	%
Age	36.03	11.02	
Gender			
Male			69.13
Female			30.43
Other			0.44
Depression (MDI)	18.06	11.66	
Problem gambling (SOGS-RA)	2.81	2.90	
Probability distortion			
LPD ($0-25\%$)	2.26	4.32	
HPD ($75-100\%$)	-5.25	5.64	
Education			
High school or less			14.34
College or bachelor			64.81
Postgraduate or professional degree			20.85
Employment status			
Employed			83.04
Student, unemployed or retired			16.96
Income			
Less than USD 10,000			12.61
From USD 10,000 to USD 59,999			65.65
More than USD 59,999			21.74
Civil status			
Single			20.00
Cohabiting			43.91
Married			36.09
Numeracy correct response			40.26

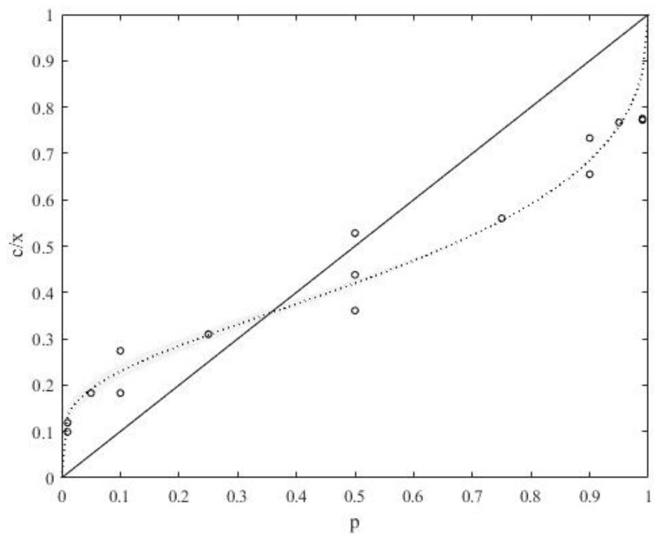
We continue by describing the probability distortion of the whole sample. Figure 4 plots the mean[14] perceived probabilities (c/x) of 230 participants for each of the prospects. The weighting function satisfactorily explained an average of 81.51% of the total variance in the choices of participants. The estimated parameters are within the expected range and similar to those in

[13]Ring et al. (2018): age: $M = 38.48$, $SD = 15.12$; female: 16%; Wejbera et al. (2017): age: $M = 33.32$, $SD = 11.55$; female: 11%.

[14]The results remain robust with the median analysis.

previous studies[15]: $\alpha = 0.441$ (95% CI = [0.422, 0.463]) and $\delta = 1.019$ (95% CI = [0.990, 1.048]). When plotted against the objective probabilities (p), the predicted probabilities produced by the weighting function replicated the typical inverted S-curve crossing the identity line at $p \approx 0.36$ (consistent with Prelec (1998)). That is, in general, individuals in our sample overweight small probabilities and underweight big probabilities in accordance with previous literature.

Figure 4: Fitted probability weighting function



Note: The dots are the mean c/x of 230 participants elicited from 15 prospects. Values of c/x above the identity (diagonal) line are characterised by overweighting of probabilities (risk-taking), and below the identity line by underweighting of probabilities (risk-averse). Risk neutrality is indicated by the identity line. Shaded areas indicate the 95% confidence interval.

To further explore gambling behaviors of respondents, we look at types and reasons for gambling. Regarding gambling types, most participants engage in strategic games (78.8%) and games of chance (75.3%).[16] In addition, 39.4% of the participants take part in financial trading. Reasons for gambling are mainly financial (60.1%), followed by recreational (55.4%), enhancement (52.4%), social (27.9%) purposes and coping strategy (12.0%). Table B2, Appendix B, reports the bivariate correlations between types (reasons) of gambling and other variables of interest (depression, probability distortion and problem gambling). Notably, there is a strong positive

[15] Bleichrodt and Pinto (2000) reported α and δ of 0.534 and delta of 1.083, respectively, in a study on 51 undergraduate students in economics, and Ring et al. (2018) 0.582 and 0.838 in a study on 74 gamblers.

[16] The proportions do not add up to 100% as there are participants who engage in multiple types of gambling activities.

relationship between depression and coping strategy. Furthermore, types (reasons) of gambling and probability distortion are not significantly associated.

4.2 Mediation tests

Table 4 presents the bivariate correlations between the variables of interest. As expected, depressive symptoms and problem gambling are strongly and positively correlated. Additionally, a significant relationship is found between problem gambling and probability distortion, such that a higher level of problem gambling leads to more overweighting of small probabilities and less underweighting of big probabilities, with the effect being stronger in the latter domain. However, depression is not associated with probability distortion, implying no mediating effect to be discovered.

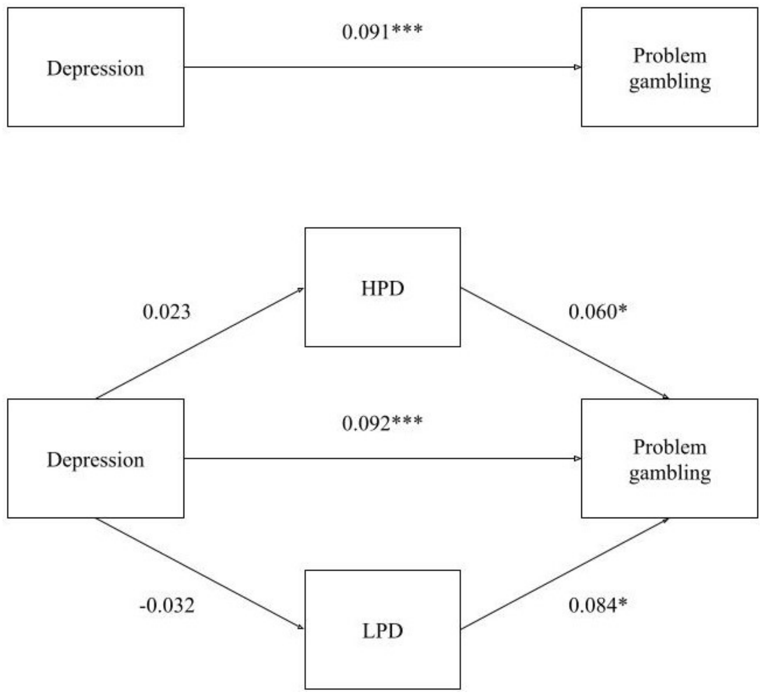
Table 4: Bivariate correlations

Measures	1	2	3	4
1. Depression (MDI)	-			
2. Problem gambling (SOGS-RA)	0.365***	-		
3. LPD ($0-25\%$)	-0.086	0.132*	-	
4. HPD ($75-100\%$)	0.047	0.174**	0.317***	-

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Figure 5 illustrates the mediation analysis with the corresponding effects for depression, low probability distortion (LPD), high probability distortion (HPD), and problem gambling, controlled for age, gender, income, education level and marital status. Full OLS estimates for covariates can be found in Table B5, Appendix B. Depression significantly accounts for 13.33% of the variations in problem gambling symptoms. The total effect of depression on problem gambling is 0.091, that is, when the depression score increases by one point, the problem gambling score increases by 0.091 points, ceteris paribus. This translates to 0.031 standard deviations increase in the problem gambling score. The finding is consistent with previous literature (Clarke, 2006; Takamatsu et al., 2015). Nevertheless, depressive symptoms are not a predictor for probability distortion, as the correlation between the two variables is not statistically significant. Consequently, probability distortion is the mediator in the depression – problem gambling relationship. That explains why the direct path from depression to problem gambling remains significant (and even increases in magnitude, particularly from 0.091 to 0.092) after LPD and HPD are included in the regression. In general, we cannot find evidence to support the second hypothesis that probability distortion is not the mediator between depression and problem gambling. This finding does not depend on the specific probability intervals that are used in the regression, as no correlation is found for other intervals (0 to 5% and 0 to 10% for LPD, 90 to 100% and 95 to 100% for HPD).

Figure 5: Mediation results

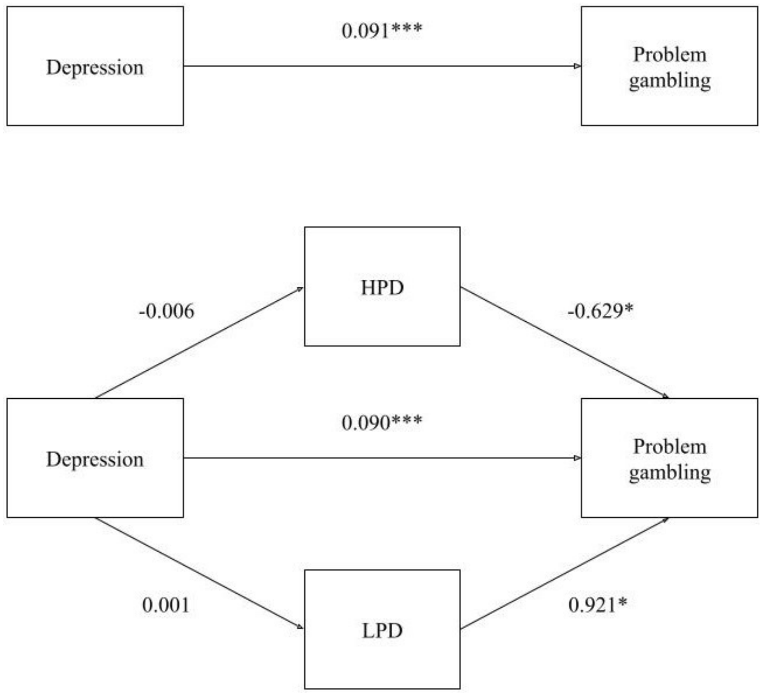


Note: Path model and OLS regression coefficients depicting the roles of HPD and LPD in mediating the effect of depression on problem gambling. HPD is the integral of $(w(p) - p)$ from 75 to 100%. LPD is the integral of $(w(p) - p)$ from 0 to 25%. * $p < 0.05$; *** $p < 0.001$.

4.2.1 Robustness check

Figure 6 reports the mediation analysis result using the secondary measure for misperception of probabilities. The null result is very much robust, as depression is not the relevant predictor for why individuals deviate from neutrality when facing risky prospects. Table B6, Appendix B, fully reports the regression outputs.

Figure 6: Mediation results from secondary measure



Note: Path model and OLS regression coefficients depicting the roles of HPD and LPD in mediating the effect of depression on problem gambling. HPD is measured by the difference between observed perceived probabilities and stated probabilities of 0.75, 0.90, 0.95, 0.99. LPD is measured by the difference between observed probabilities and stated probabilities of 0.01, 0.05, 0.10, 0.25. * $p < 0.05$; *** $p < 0.001$.

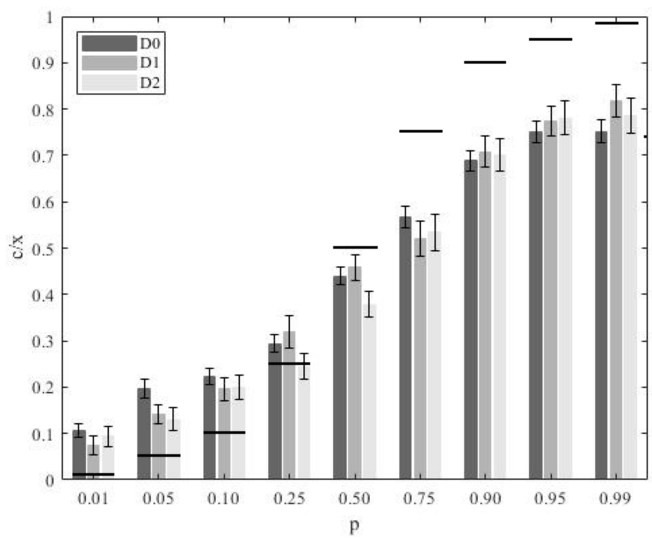
We now continue with the analysis on probability distortion between depression groups and problem gambling groups, followed by an exploratory analysis of the non-linear relationship between depression and probability distortion.

4.3 Probability distortion between depression groups

The MDI questionnaire has a very high internal consistency (Cronbach's alpha) of 0.949. Based on MDI total score, 58.3% ($n = 134$) of the sample are categorized as non-depressed (control group D0, $M = 9.28$, $SD = 4.97$), 20.8% ($n = 48$) as mild-to-moderately depressed (group D1, $M = 25.35$, $SD = 2.74$), 20.8% ($n = 48$) as severely depressed (group D2, $M = 34.92$, $SD = 4.25$). The distribution of the MDI total score can be found in Figure B1, Appendix B.

First, we compare the c/x between the three depression groups across the 15 prospects. For prospects with repeated probabilities $(0.01, 0.10, 0.50, 0.90, 0.99)$, the mean value of c/x was used (as in Ring et al. (2018)). Figure 7 shows the c/x against the objective probabilities (p) between the three groups. From the figure, no consistent pattern is displayed between the depression groups. The non-depressed significantly overweights c/x at 5% compared to the other groups, however, we find no indication that probability distortion varies systematically with participants' level of depression.

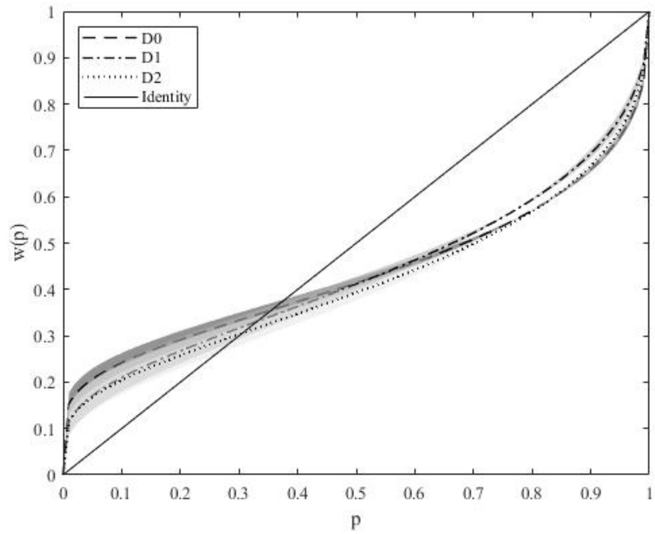
Figure 7: Perceived probabilities between depression groups



Note: Error bars indicate the standard errors of the mean. Horizontal lines indicate neutrality, where perceived probabilities equal objective probabilities.

Next, we fit the observed data to the weighting function by Prelec (1998). The function explains 79.38%, 86.37%, and 82.79% of the variances for the non-depressed, the mild-to-moderate depression, and the severe depression group, respectively. The corresponding estimated α are 0.398 (95% CI = [0.371; 0.424]), 0.470 (95% CI = [0.426; 0.513]), and 0.443 (95% CI = [0.399; 0.485]), and analogously for δ are 1.012 (95% CI = [0.980; 1.059]), 1.055 (95% CI = [0.993; 1.116]), and 1.099 (95% CI = [1.031; 1.166]). In congruence with Figure 8, there are heavy overlappings in the 95% CIs estimates for each of the groups. Looking at the parameters, D0 has both the lowest mean α and δ, although the difference is marginal. Further, the trend in parameters appears increasing with depression groups, however, with significant overlapping. Generally, this reflects a less pronounced S-shape with increased depression and shifts the weighting function downwards.

Figure 8: Weighting function between depression groups



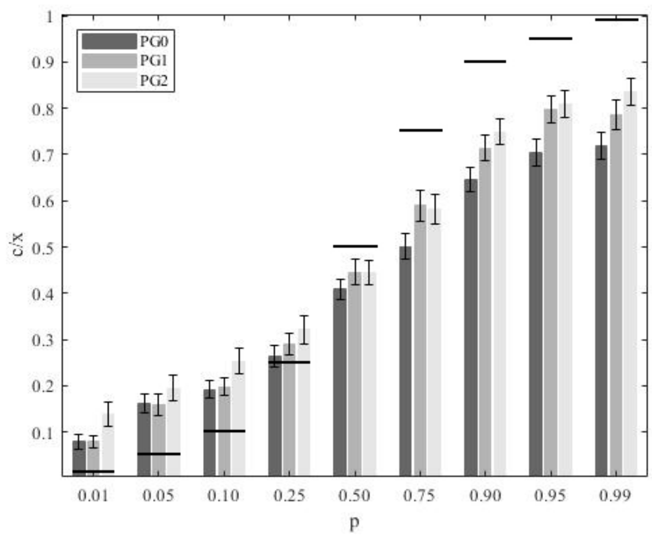
Note: The fitted curves show the Prelec weighting function using parameters from group non-linear regression. Shaded areas indicate the 95% confidence interval.

4.4 Probability distortion between gambling groups

The SOGS-RA questionnaire has an internal consistency (Cronbach's alpha) of 0.856. From the SOGS-RA scores, 41.7% ($n = 96$) of the sample are categorized as gamblers with no problem (control group PG0, $M = 0.43$, $SD = 0.48$), 29.1% ($n = 67$) as at risk of problem gambling (group PG1, $M = 2.36$, $SD = 0.50$), and 29.6% ($n = 68$) as pathological gamblers (group PG2, $M = 6.60$, $SD = 2.33$). The distribution of the SOGS-RA score can be found in Figure B2, Appendix B.

First, we compared the c/x and the stated probabilities from the 15 prospects. Generally, the certainty equivalents increase with the degree of problem gambling, with the differences being stark between PG0 and PG2. As shown in Figure 9, the pathological gambling group overweights both small probabilities and big probabilities relative to the group with no problem gambling. Whilst this means pathological gamblers misperceived the small probabilities ($p \leq 0.25$) more, they have a more precise perception of big probabilities ($p > 0.5$). In other words, their behaviors show a consistent shift toward risky options (similar to findings from Ligneul et al. (2012)). Notably, pathological gamblers also show consistently higher variance in misperception of low probabilities ($p \leq 0.25$) compared to the other two groups.

Figure 9: Perceived probabilities between gambling groups

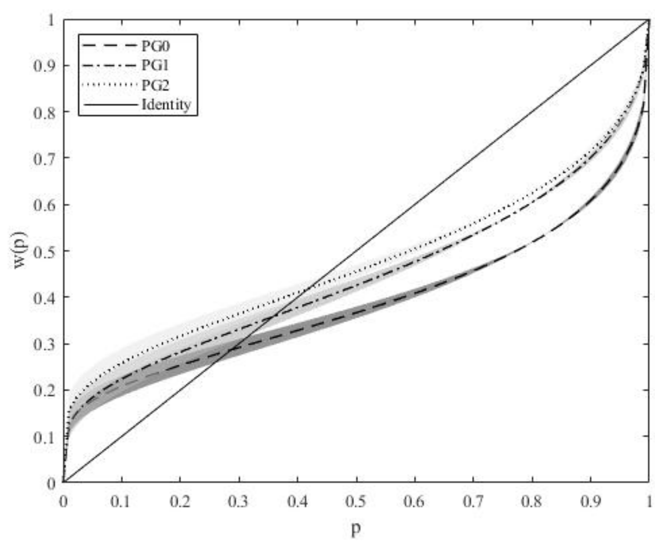


Note: Error bars indicate the standard errors of the mean. Horizontal lines indicate neutrality, where perceived probabilities equal objective probabilities.

Next, we analyse results from fitting the observed data to the probability weighting function. The weighting function performs an adequate fit for each group. Particularly, it explains 78.94%, 83.18%, 83.73% of the variances for the control group (PG0), the at-risk group (PG1) and pathological gamblers group (PG2). The estimated α are 0.373 (95% CI = [0.345; 0.401]), 0.467 (95% CI = [0.428; 0.506]), and 0.453 (95% CI = [0.413; 0.494]) for PG0, PG1 and PG2, respectively, and similarly for δ are 1.150 (95% CI = [1.099; 1.200]), 1.014 (95% CI = [0.961; 1.067]), and 0.928 (95% CI = [0.879; 0.977]). The differences between α and δ are statistically significant as the 95% CI estimates do not overlap when comparing PG0 with PG1, and PG0 and PG2. There are more elevations (smaller δ) observed in the at-risk and the pathological groups, indicating a preference (attractiveness) for risky prospects relative to the control group. Interestingly, gamblers with no problem appears to be less sensitive to the change in probabilities (discriminability) than those at risk and pathological gamblers, as its estimated α is smaller. This is inconsistent with Ring et al. (2018) who suggest the opposite, and with Ligneul et al. (2012), who find no difference in probability sensitivity between gambling groups.

Looking at Figure 10, regarding the small probabilities domain ($p < 0.3$), we observed a clear difference between the control group and the pathological group. However, there are overlappings in the 95% CIs estimates between the control and at-risk group, and between the at-risk and pathological group. Intuitively, this suggests the overweighting of small probabilities bias is more severe with higher degrees of problem gambling. In terms of the big probabilities domain, we see a more pronounced difference in the extent to which the three groups deviate from the identity line. In the big probabilities domain, the integrals are expected to be negative, as the weighting function is below the identity line. Thus, the positive and significant coefficients (from Table 4) for the integral variables imply the reduced distance from the perceived to the objective probabilities. In other words, pathological gamblers are less prone to big probabilities underweighting, as they naturally require greater certainty equivalents to give up gambles with high winning chances. Analogously, the inflection points where the groups change from overweighting to underweighting probabilities are also increasing with higher degrees of problem gambling (PG0: $\tilde{p} \approx 0.28$; PG1: $\tilde{p} \approx 0.36$; PG2: $\tilde{p} \approx 0.42$;). This further suggests that the problem gambling groups (PG1 and PG2) value risks more than the control group, as the switching behavior also implies a risk avoiding attitude (Ring et al., 2018).

Figure 10: Weighting function between gambling groups

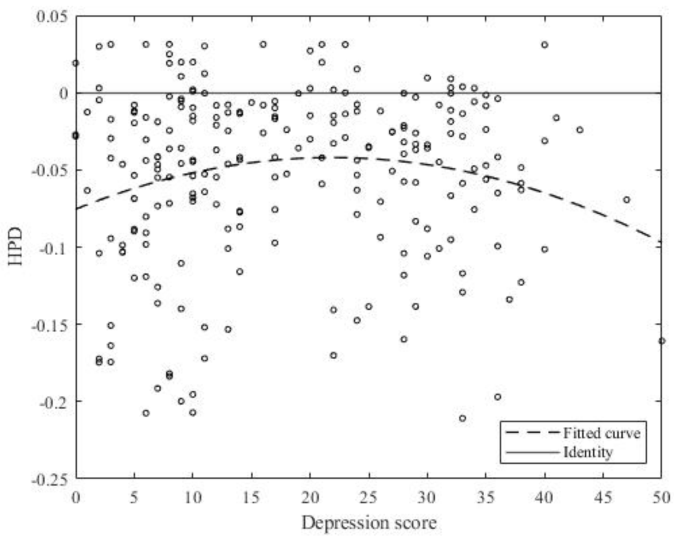


Note: The fitted curves show the Prelec weighting function using parameters from group non-linear regression. Shaded areas indicate the 95% confidence interval.

4.5 Ex-post analysis

In this part, we present an exploratory analysis with respect to the correlation between depression and misperception of probabilities. A quadratic relationship is found between depressive symptoms and high probability distortion. In particular, non-depressed participants and severely depressed are more prone to high probability distortion, relative to their mild-to-moderately depressed counterparts. In Figure 11, the gap between perceived probabilities and objective probabilities for the range from 75 to 100% gets narrower as the depression score goes from 0 to ca. 25 (corresponding to individuals in the non-depressed and the first half of mildly depressed groups), and expands when the score is above 25 (second half of mildly depressed, moderately and severely depressed groups). Table B7, Appendix B, reports the regression output when a squared term of depression is incorporated in the equation.

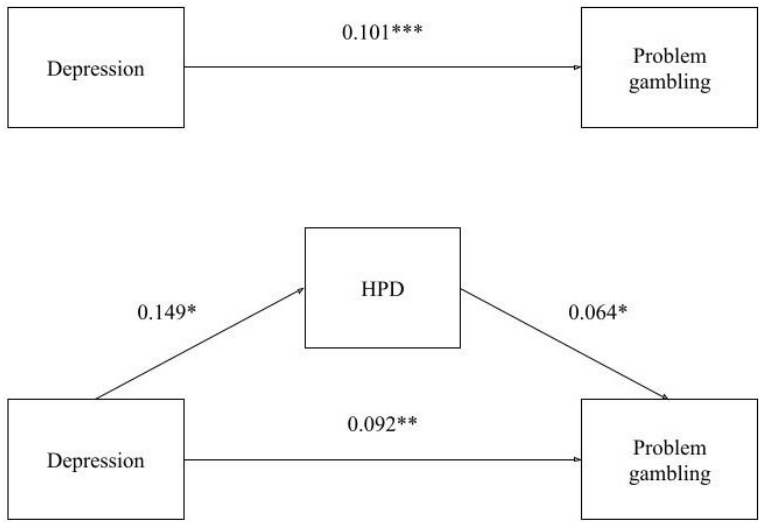
Figure 11: Quadratic relationship between depression and HPD



Note: HPD is the integral of $(w(p) - p)$ from 75 to 100%. The identity line at $HPD = 0$ indicates no probability distortion. Values below this line suggest underweighting and values above this line suggest overweighting of probabilities.

We continue by conducting the mediation analysis on the subgroup of individuals with a depression score below 25 ($n = 159$). As predicted from Figure 12, in this particular subgroup, higher levels of depression is associated with a more precise perception of big probabilities (demonstrated by the positive coefficient between the two variables), and subsequently the perception of big probabilities can predict the degree of problem gambling. After controlling for high probability distortion, the magnitude of the effect from depression on problem gambling decreases from 0.101 to 0.092, nevertheless it is still significant at the 5% level. The bootstrapping method with 599 replications reveals that the indirect effect is not statistically significant at the 5% level (95% CI = [-0.002, 0.021]). The full OLS regression outputs are reported in Table B8, Appendix B.

Figure 12: Subgroup mediation results



Note: Path model and OLS regression coefficients depicting the roles of HPD in mediating the effect of depression on problem gambling. HPD is the integral of $(w(p) - p)$ from 75 to 100%. The analysis is conducted on a subgroup of participants whose depression score are below 25. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

5 Discussion and final remarks

This study aims to assess if the presence of misperception of probabilities could have accounted for the associations between depressive symptoms and problem gambling.

The summary of the main findings of this study is as follows. First, although we are able to confirm the positive association between depression and problem gambling, we find no empirical evidence to postulate that misperception of probabilities is a mediator for this relationship. This conclusion comes from the null linear correlation between depression and probability distortion. Second, group analysis on the probability weighting function suggests that there is a global shift toward risk in the at-risk and pathological groups compared to the group with no problem gambling. That is, not only do higher degrees of problem gambling lead to overweighting of small probabilities, it also leads to more "overweighting" of big probabilities (i.e., underweighting of big probabilities to a lesser extent), and more sensitivity to change in probabilities. Finally, a quadratic correlation between depression and misperception of high probabilities has been established. Particularly, participants perceive probabilities more accurately when the depression score increases to 25, but beyond that point, individuals start to further deviate from neutrality.

We hereby discuss the first finding regarding the mediating role of probability distortion in the depression – problem gambling relationship. The core matter lies in the underlying assumption that depression (the predictor) has a linear effect on the mediator (probability distortion), while in fact we do not observe such a trend from our dataset. This finding of no correlation between depression and perception of probabilities is contradictory to the result of Kliger and Levy (2008), who established that sources of depression (seasonal affective disorder and cloudiness) increase distortion to the weighting function of Tversky and Kahneman (1992) among market actors. Nevertheless, given the quadratic correlation between depression and high probability distortion discovered in this paper, one potential for future study could be to incorporate this nonlinearity into the mediation framework, or to look at different subgroups based on depression level.

We further discuss the method of examining probability distortion. Thus far, studies exploring the same topic using different probability weighting functions mainly focus on the comparison of estimated parameters between groups (Kliger & Levy, 2008; Ligneul et al., 2012; Cobb-Clark, Dahmann, & Kettlewell, 2019; Ring et al., 2018). We propose the use of integrals as one complementary method for a number of reasons. First, it is consistent with results from the group comparisons. Take the fitted weighting function for depression groups for example: a direct comparison shows no statistically significant difference in the estimated δ and α between the groups (Figure 8). OLS regression using integrals for different probabilities ranges draws the same conclusion. Second, this method offers a more straightforward and intuitive interpretation, as it incorporates both parameters into one quantity. The absolute value of the integrals demonstrates the extent of deviation (distortion) from neutrality, and the sign of the integrals exhibit the type of deviation (overweighting or underweighting). Third, this might as well be used as a continuous variable in the investigation of probability distortion in other relationships, for instance, as a potential mediator.

Regarding the second finding, it is well known that gamblers are more likely to put excessive weight to small probabilities, however, it is not fully elucidated how they perceive big probabilities. Our finding, besides confirming the former hypothesis, contributes an insight to the latter: that is, heavy (problem) gamblers underweight big probabilities to a lesser extent, relative to their healthy counterparts. This questions the "distortion hypothesis" which posits that pathological gamblers suffer from a probability weighting function that is more distorted, hence increased in insensitivity toward changes (Kahneman & Tversky, 1979; Trepela, Fox, & Poldrack, 2005), as our study shows that the pathological group (PG2) has a higher α than the control group (PG0).[17] Our finding suggests that although problematic gamblers still present a prototypical small (big) probabilities overweighting (underweighting), their weighting function systematically shifts upward in comparison to the no problem gambling groups (PG0 and PG1). This implies that risk-seeking in problem gambling is strongly linked to a greater attractiveness of risk, and/or greater optimism (confidence) about risky events, and so the elevation parameter (δ) should also be considered when assessing risk-seeking behaviors from the weighting function. This "elevation hypothesis" has also been studied in Ligneul et al. (2012), as they observe a significant difference in δ, rather than α, between healthy and pathological gamblers. For that, we first recommend that the two-parameter weighting function family is more appropriate in future studies on similar research areas, as it allows the segregation of sensitivity (distortion) and attractiveness (elevation). Second, given the lack of consensus in high probabilities perception, it is more insightful and interesting to investigate the two domains separately instead of just exploring the full probability distribution.

The quadratic correlation between depression and probability distortion can be drawn upon the theory of "depressive realism" (Alloy & Abramson, 1979, 1998). A sizable literature posits that depressed individuals possess a more realistic perception of their role, abilities, and limitations (see Moore and Fresco (2012) for meta-analytic reviews). The experiment from Alloy and Abramson (1979) find that depressed students tend to be accurate across conditions that vary in contingency whilst non-depressed students overestimate their control of positive outcomes and underestimate their control of negative outcomes. However, depression leading to more accurate perception is not necessarily a linear phenomenon. Soderstrom, Davalos, and Vázquez (2011) find evidence buttressing the view that the level of depression accounts for depressive realism, as in an experiment testing memory performance, they find that mild depression is associated with better calibration than non-depression. However, as moderate depression and non-depression show no differences in performance, there appears a threshold for the "sadder but wiser" phenomenon. Hence, the quadratic effect of depression on high probability distortion found in this study lends some supports to this argument. Mild depression may shed the rose-tinted spectacles and Pollyanna optimism[18], thus enabling humans to see things more accurately, and judge them accordingly.

[17] Recall that a smaller α results in a more distorted weighting function.

[18] The Pollyanna principle is the phenomenon where the mind subconsciously focuses on pleasant items whilst at the conscious level, it tends to remember the unpleasant ones more accurately (Matlin & Stang, 1978).

Next, it is essential to discuss the main limitations of the study. These limitations come from the violations of the important assumptions outlined in the method. First, reverse causality is an issue, as it is uncertain if depression can strengthen the tendency to engage in gambling activities, or if it is an emotional reaction to losses and psychological problems caused by regular gambling. However, a couple of studies give tentative support to the hypothesis that depression is a predictor rather than a consequence from gambling, as given the appropriate environment, depressed people are more likely to gamble to release worries and frustrations (Derevensky & Gupta, 1998; Abbott & Volberg, 1996; Raviv, 1993). Second, it is not clear whether the mediator (probability distortion) is the cause or the result of the outcome (problem gambling). Nevertheless, it is more plausible for individuals with a defective perception of probabilities to be more involved in gambling in the first place, as suggested in some studies that investigate the relationship between misperception of probabilities and risk-taking (Snowberg & Wolfers, 2010; Barseghyan et al., 2013). A longitudinal dataset would be more auspicious regarding this matter, as it may provide a dynamic setting, and/or a good instrumental variable which is missing in this study.[19]

The second limitation is omitted variable bias. We hope to mitigate this threat by controlling for some basic individual factors and the numeracy and risk literacy test that may affect the variables of interest. However, we do not claim to completely rule out this problem, and this is especially deleterious for mediation analysis as the presence of a confounder can mislead the mediating mechanisms (Valente, Pelham, Smyth, & MacKinnon, 2017). For example, there may be other cognitive dysfunctions that cause depression and misperception of probabilities, which may undermine the conclusion on the mediation effect of probability distortion. One approach to address this confounding bias is to conduct a randomized experiment, where subjects are randomly induced with different levels of negative, and/or positive emotions (e.g., by priming (Cohn & Maréchal, 2016) or the use of music or movies (Innes-Ker, 2015)).

Third, all variables are likely to be measured with measurement errors, because (i) they are internal, psychological variables, and (ii) a survey measurement is not perfect in eliciting real behaviors. This is especially problematic with the mediator in the Baron and Kenny (1986) framework, as mentioned in the theoretical framework. There are a few approaches to minimize

[19]The Swedish Longitudinal Gambling Study (Swelogs) could provide promising insights on the relationship between mental health and problem gambling (Folkhälsomyndigheten, 2020), however, due to the sensitiveness of the information, we could not get access to it within the scope of this thesis.

this error, however, they were not possible for us, given the short timeline and the budget constraints of the study. The first method is to construct multiple indicators of the mediator, i.e., use other methods to measure how individuals perceive probabilities. For instance, questions on how subjects estimate the chances of future events can be integrated. However, the length of the survey and the attention span of participants may impose a constraint to this approach. The second approach is from Gillen, Snowberg, and Yariv (2019), which is to use Obviously Related Instrumental Variables (ORIV) where the variable is measured twice (using different numerical values), and the duplicate observation is used as an instrument in 2SLS (assuming measurement error is independent across elicitations). This technique can be applied by sending the prospects with different payoffs and probabilities to the same participants after an amount of time (e.g., one month).

Finally, as the survey was carried out online, we could not supervise participants, or provide them with extra guidance and instructions. However, considering the budget constraints of the study, this is the most appropriate method that we could use to collect data. To make sure the survey is easy to follow, we ran several pilots on graduate students at the University of Gothenburg. Furthermore, to minimize adverse behaviors from participants, we conducted the survey on a professional platform for researchers to recruit survey participants, and focused on participants who are relatively experienced in taking surveys. We are aware that this is a limitation to the sampling procedure, however, should we remove this filter from the participation screening process, we would need a much greater sample size, which is not feasible for this project.

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Appendix A

Survey consent form

Welcome to our study!

This is a study on economic decision-making, gambling and mental health. The survey takes about 16 minutes to complete.

For completing the study you will be paid £2.30. There is a chance to receive a bonus in one part of the survey. To be qualified for the study and get compensated, you must be above 18 years old, have regularly engaged in gambling activities in the last 6 months and follow all instructions. The money will be transferred to your Prolific account within 7 days from completion of the survey.

We will not ask questions on your personal identification such as your name, your email address or collect your IP address. All information gathered is kept strictly anonymous. No parties, including researchers, Prolific or Qualtrics, can identify an individual based on his/her answers, or know whether or not an individual participated in the study.

You are only allowed to take the study once. If you participate more than once, your work will be rejected.

Participation is voluntary, and you are free to withdraw from the study at any time without any impact on your involvement in future services for Prolific. However, refusal to participate or withdrawal from the study will result in no compensation. By agreeing to participate below, you are indicating that you have read the description of the study, are over the age of 18, and that you agree to the terms described.

If you have any questions or concerns about this study, please send Chi Nguyen a message on Prolific.

Table A1: Summary of prospects

No.	Prospect	Description
1	P($50, 10%; 0)	What would you prefer: A gamble with a 10-percent chance of receiving $50 and 90-percent chance of receiving nothing, OR the following amounts as a sure payment?
2	P($50, 90%; 0)	What would you prefer: A gamble with a 50-percent chance of receiving $50 and 50-percent chance of receiving nothing, OR the following amounts as a sure payment?
3	P($50, 90%; 0)	What would you prefer: A gamble with a 90-percent chance of receiving $50 and the 10-percent chance of receiving nothing, OR the following amounts as a sure payment?
4	P($100, 5%; 0)	What would you prefer: A gamble with a 5-percent chance of receiving $100 and 95-percent chance of receiving nothing, OR the following amounts as a sure payment?
5	P($100, 25%; 0)	What would you prefer: A gamble with a 25-percent chance of receiving $100 and 75-percent chance of receiving nothing, OR the following amounts as a sure payment?
6	P($100, 50%; 0)	What would you prefer: A gamble with a 50-percent chance of receiving $100 and 50-percent chance of receiving nothing, OR the following amounts as a sure payment?
7	P($100, 75%; 0)	What would you prefer: A gamble with a 75-percent chance of receiving $100 and 25-percent chance of receiving nothing, OR the following amounts as a sure payment?
8	P($100, 95%; 0)	What would you prefer: A gamble with a 95-percent chance of receiving $100 and 5-percent chance of receiving nothing, OR the following amounts as a sure payment?
9	P($200, 1%; 0)	What would you prefer: A gamble with a 1-percent chance of receiving $200 and 99-percent chance of receiving nothing, OR the following amounts as a sure payment?
10	P($200, 10%; 0)	What would you prefer: A gamble with a 10-percent chance of receiving $200 and 90-percent chance of receiving nothing, OR the following amounts as a sure payment?
11	P($200, 50%; 0)	What would you prefer: A gamble with a 50-percent chance of receiving $200 and 50-percent chance of receiving nothing, OR the following amounts as a sure payment?
12	P($200, 90%; 0)	What would you prefer: A gamble with a 90-percent chance of receiving $200 and 10-percent chance of receiving nothing, OR the following amounts as a sure payment?
13	P($200, 99%; 0)	What would you prefer: A gamble with a 99-percent chance of receiving $200 and 1-percent chance of receiving nothing, OR the following amounts as a sure payment?
14	P($400, 1%; 0)	What would you prefer: A gamble with a 1-percent chance of receiving $400 and 99-percent chance of receiving nothing, OR the following amounts as a sure payment?
15	P($400, 99%; 0)	What would you prefer: A gamble with a 99-percent chance of receiving $400 and 1-percent chance of receiving nothing, OR the following amounts as a sure payment?

Table A2: Single-item Berlin Numeracy Test

Description: Out of 1000 people in a small town 400 are members of a book club. Out of these 400 members 100 are men. Out of the 600 inhabitants that are not in the book club 400 are men. What is the probability that a randomly drawn man is a member of the book club?
Correct answer: 20%

Table A3: Major Depression Inventory (MDI)

No.	**Description**						
	Over the last six months, how often have you been bothered by the following problem...	All the time	Most of the time	More than half of the time	Less than half of the time	Some of the time	At no time
1	Felt low in spirits or sad?	5	4	3	2	1	0
2	Lost interest in your daily activities?	5	4	3	2	1	0
3	Felt lacking in energy and strength?	5	4	3	2	1	0
4	Felt less self-confident?	5	4	3	2	1	0
5	Had bad conscience or feelings of guilt?	5	4	3	2	1	0
6	Felt that life wasn't worth living?	5	4	3	2	1	0
7	Had difficulty in concentrating?	5	4	3	2	1	0
8	Felt very restless?	5	4	3	2	1	0
9	Felt subdued or slowed down?	5	4	3	2	1	0
10	Had trouble sleeping at night?	5	4	3	2	1	0
11	Suffered from reduced appetite?	5	4	3	2	1	0
12	Suffered from increased appetite?	5	4	3	2	1	0

Note: For items 8-9 and 11-12 only the highest response is used to construct the depression variable.

Table A4: South Oaks Gambling Screen: Revised for Adolescents (SOGS-RA)

No.	Description	Every time	Most of the time	Some of the time	Never
	Over the last six months, have you experienced the following...				
1	How often have you gone back another day to try and win back money you lost gambling?	1	1	0	0

No.	Description	Yes	No
2	When you were betting, have you ever told others you were winning money when you were not?	1	0
3	Has your betting money ever caused any problems for you such as arguments with family and friends, or problems at school?	1	0
4	Have you ever gambled more than you have planned to?	1	0
5	Has anyone criticized your betting, or told you that you had a gambling problem whether you thought it true or not?	1	0
6	Have you ever felt bad about the amount of money you bet, or about what happens when you bet money?	1	0
7	Have you ever felt like you would like to stop betting, but did not think you could?	1	0
8	Have you ever hidden from family or friends any betting slips, lottery tickets, money that you won, or any signs of gambling?	1	0
9	Have you had money arguments with family or friends that centered on gambling?	1	0
10	Have you borrowed money to bet and not paid it back?	1	0
11	Have you ever skipped or been absent from school or work due to betting activities?	1	0
12	Have you borrowed money or stolen something in order to bet or to cover gambling activities?	1	0

Table A5: Covariates

No.	**Description**	**Choice alternatives**
1	Please enter your age:	Fill in box
2	Please enter your gender:	Male/Female/Other
3	Please select the highest degree or level of school you have completed:	Less than high school degree/High school graduate/ Some college, but no degree/Bachelor's degree/ Master's degree/Professional degree/Doctorate
4	Please select your current employment status:	Student/Employed/Unemployed/Self-employed/ Retired
5	Please report your gross annual income (in USD):	Less than \$10,000/\$10,000 - \$19,999/\$20,000 - \$29,999/ \$30,000 - \$39,999/\$40,000 - \$49,999/\$50,000 - \$59,999/ \$60,000 - \$69,999/\$70,000 - \$79,999/\$80,000 - \$89,999/ \$90,000 - \$99,999/More than \$150,000
6	Please enter your marital status:	Single/Cohabiting/Married
7	Please enter the number of children you have:	0/1/2/3/More than 3
8	Please select the types of gambling activities you have engaged in within the last six months – either online or offline (select all that apply):	Strategic games (e.g., poker, blackjack, card games, sports betting, horse (or other animals) betting)/ Games of chance (e.g., lottery, bingo, dice games, slot machines, scratch cards)/Financial trading (e.g., stocks, derivatives, commodities, cryptocurrencies)/Other gambling activities (please specify)
9	Please select the main reason for your gambling activities in the last six months – either online or offline (select all that apply):	Social (e.g., something that is engaged in with friends and family)/Financial (e.g., for the chance of winning large amounts of money)/Enhancement (e.g., for the excitement)/Recreational (e.g., to fill time)/Coping (e.g., to relieve tension)/Other reasons (please specify)

Appendix B

Table B1: Characteristics by prospect sets

Variables	Set A ($n = 59$)	Set B ($n = 58$)	Set C ($n = 58$)	Set D ($n = 55$)	p-value
Age	33.36 (11.74)	37.17 (10.34)	36.01 (10.70)	37.72 (11.00)	0.054
Female (%)	27.11	35.09	25.86	34.54	0.596
MDI score	20.16 (11.31)	16.19 (12.70)	19.32 (11.32)	16.44 (11.04)	0.979
SOGS-RA score	2.83 (2.85)	2.76 (2.96)	2.90 (3.19)	2.75 (2.63)	0.094
Probability distortion					
LPD ($0 - 25\%$)	2.61 (4.96)	2.80 (4.03)	1.26 (3.36)	2.34 (4.68)	0.114
HPD ($75 - 100\%$)	-5.35 (6.08)	-4.76 (5.08)	-5.65 (5.71)	-5.23 (5.72)	0.858
Education (%)					
High school or less	15.25	15.52	12.08	15.69	0.988
College or bachelor	71.67	52.54	72.88	64.15	0.078
Postgraduate or professional degree	13.08	31.94	15.04	20.16	0.046
Employment status (%)					
Employed	79.66	86.20	82.76	82.14	0.698
Student, unemployed or retired	20.34	13.80	17.24	17.86	0.698
Income group	3.92 (3.05)	3.38 (2.59)	3.47 (2.56)	3.18 (2.69)	0.616
Civil status (%)					
Single	47.46	35.59	43.10	48.43	0.356
Cohabiting	11.67	20.34	36.21	10.71	0.002
Married	40.87	44.07	20.69	40.86	0.038
Numeracy correct response (%)	42.37	36.20	46.55	35.71	0.586

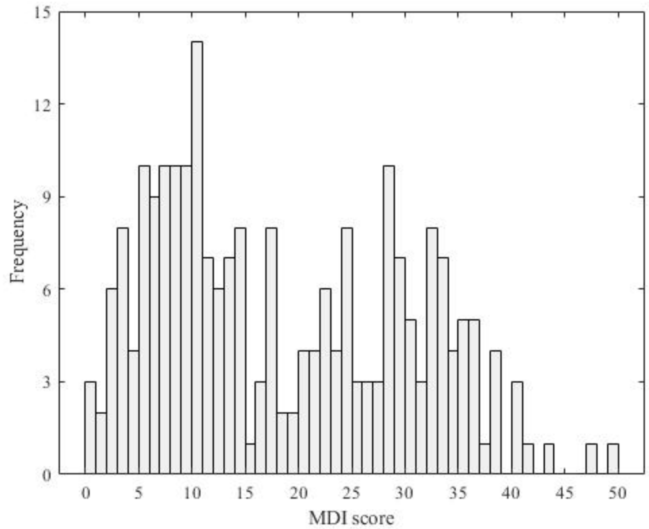
Note: Groups were compared by the mean ranks of independent-sample Kruskal Wallis tests. Standard deviation is in parentheses.

Table B2: Bivariate correlations

	1	2	3	4	5	6	7	8	9	10	11	12
1. Games of chance	-											
2. Strategic games	-0.199**	-										
3. Financial trading	-0.052	0.093	-									
4. Coping	0.090	0.031	0.081	-								
5. Enhancement	0.062	0.125	0.034	0.085	-							
6. Financial	-0.009	0.102	0.287***	0.082	0.001	-						
7. Recreational	0.158*	0.114	-0.015	0.036	0.015	-0.146*	-					
8. Social	0.090	0.136*	0.106	0.092	0.109	-0.028	0.072	-				
9. Depression (MDI)	-0.006	0.008	0.118	0.224***	-0.062	0.083	0.025	-0.097	-			
10. Problem gambling (SOGS-RA)	0.066	0.010	0.050	0.272***	0.037	0.189**	-0.143*	-0.145*	0.365***	-		
11. LPD $(0-25\%)$	0.007	-0.031	-0.035	0.008	-0.100	-0.086	-0.034	-0.041	-0.086	0.132*	-	
12. HPD $(75-100\%)$	-0.059	0.051	-0.126	0.024	-0.068	-0.036	-0.021	-0.106	0.047	0.174**	0.317***	-

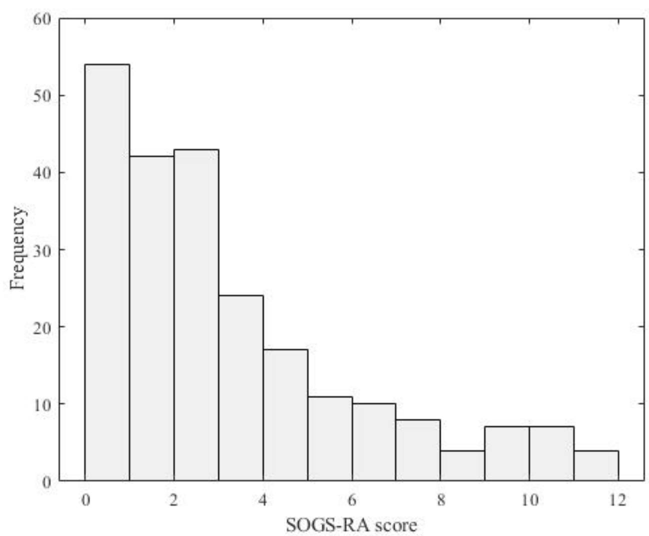
Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Figure B1: MDI total score distribution



Note: The x-axis indicates the MDI total score from the depression questionnaire. The y-axis indicates the number of individuals with corresponding score.

Figure B2: SOGS-RA total score distribution



Note: The x-axis indicates the SOGS-RA total score from the problem gambling questionnaire. The y-axis indicates the number of individuals with corresponding score.

Table B3: Characteristics of depression groups

Variables	D0	D1	D2	p-value
Age	37.83 (11.34)	34.73 (9.96)	32.33 (10.19)	0.007
Female (%)	29.85	39.58	23.40	0.223
MDI score	9.28 (4.97)	25.35 (2.74)	34.92 (4.25)	<0.001
SOGS-RA score	2.11 (2.43)	2.90 (2.56)	4.63 (3.57)	<0.001
Probability distortion				
LPD ($0-25\%$)	2.62 (4.53)	1.93 (3.77)	1.58 (4.20)	0.209
HPD ($75-100\%$)	-5.40 (5.93)	-4.69 (5.05)	-5.39 (5.42)	0.841
Education (%)				
High school or less	15.67	14.58	10.20	0.645
College or bachelor	61.19	66.67	75.51	0.194
Postgraduate or professional degree	23.14	18.75	14.29	0.258
Employment status (%)				
Employed	86.57	77.08	77.55	0.187
Student, unemployed or retired	13.43	22.92	22.45	0.246
Income group	3.89 (2.73)	2.87 (2.62)	2.98 (2.66)	0.016
Civil status (%)				
Single	32.08	62.50	57.14	<0.001
Cohabiting	21.65	14.58	20.40	0.574
Married	46.27	22.92	22.46	<0.001
Numeracy correct response (%)	35.82	37.50	55.10	0.057

Note: Groups were compared by the mean ranks of independent-sample Kruskal Wallis tests. Standard deviation is in parentheses.

Table B4: Characteristics of gambling groups

Variables	PG0	PG1	PG2	p-value
Age	37.84 (11.15)	36.01 (10.55)	33.46 (10.93)	0.029
Female (%)	40.00	26.87	20.90	0.025
MDI score	14.49 (11.13)	18.12 (11.61)	23.02 (10.76)	<0.001
SOGS-RA score	0.44 (0.50)	2.36 (0.48)	6.6 (2.3)	<0.001
Probability distortion				
LPD ($0-25\%$)	1.92 (3.99)	1.98 (3.44)	2.99 (5.38)	0.521
HPD ($75-100\%$)	-6.46 (5.92)	-4.63 (5.65)	-4.16 (4.92)	0.014
Education (%)				
High school or less	16.66	16.42	8.95	0.310
College or bachelor	57.29	70.15	72.06	0.092
Postgraduate or professional degree	26.05	13.43	18.99	0.121
Employment status (%)				
Employed	83.33	79.10	85.29	0.622
Student, unemployed or retired	16.67	20.90	14.71	0.494
Income group	3.79 (2.84)	3.30 (2.46)	3.25 (2.82)	0.366
Civil status (%)				
Single	39.58	49.25	44.78	0.472
Cohabiting	25.00	19.40	13.43	0.177
Married	35.42	31.35	41.79	0.489
Numeracy correct response (%)	34.38	38.81	50.00	0.128

Note: Groups were compared by the mean ranks of independent-sample Kruskal Wallis tests. Standard deviation is in parentheses.

Table B5: Mediation regression outputs

	Hypothesis 1	**Hypothesis 2**	**Hypothesis 3**	
	PG	PG	LPD	HPD
$depression$	0.091***	0.092***	-0.032	0.023
	(0.015)	(0.015)	(0.024)	(0.032)
LDP $(0-25\%)$		0.085*		
		(0.043)		
HPD $(75-100\%)$		0.060*		
		(0.033)		
age	-0.021	-0.020	-0.017	-0.004
	(0.017)	(0.017)	(0.028)	(0.037)
$female$	-0.786*	-0.797*	0.382	-0.294
	(0.389)	(0.384)	(0.623)	(0.837)
$employed$	0.332	0.333	0.429	-0.575
	(0.523)	(0.515)	(0.837)	(1.125)
$college\ or\ bachelor$	0.426	0.523	-0.658	-0.734
	(0.549)	(0.541)	(0.874)	(1.175)
$postgraduate\ or\ professional\ degree$	0.246	0.372	-0.687	-1.260
	(0.651)	(0.642)	(1.039)	(1.399)
$single$	-1.106**	-0.957*	-1.537*	-0.584
	(0.404)	(0.402)	(0.646)	(0.868)
$income$	-0.042	-0.054	0.137	0.0352
	(0.075)	(0.074)	(0.120)	(0.162)
_cons	2.080	2.083	3.193	-4.138
	(1.030)	(1.035)	(1.645)	(2.210)
Observations	229	229	229	229
Adjusted R^2	0.161	0.187	0.025	-0.025

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Bootstrapping standard error is in parentheses.

Table B6: Mediation regression outputs from secondary measurement

	Hypothesis 1	**Hypothesis 2**	**Hypothesis 3**	
	PG	PG	LPD	HPD
$depression$	0.091***	0.090***	0.001	-0.006
	(0.015)	(0.015)	(0.003)	(0.004)
LDP (differences squared)		0.921*		
		(0.392)		
HPD (differences squared)		-0.629		
		(0.280)		
age	-0.021	-0.021	-0.002	-0.002
	(0.017)	(0.017)	(0.003)	(0.004)
$female$	-0.786*	-0.757*	0.043	0.108
	(0.389)	(0.384)	(0.065)	(0.093)
$employed$	0.332	0.317	0.044	0.037
	(0.523)	(0.514)	(0.087)	(0.125)
$college\ or\ bachelor$	0.717	0.820	-0.082	0.044
	(0.589)	(0.579)	(0.091)	(0.131)
$postgraduate\ or\ professional\ degree$	0.278	0.458	-0.120	0.104
	(0.702)	(0.689)	(0.108)	(0.156)
$single$	-1.106**	-0.967*	-0.164*	0.003
	(0.404)	(0.402)	(0.067)	(0.096)
$income$	-0.042	-0.074	0.023	-0.021
	(0.075)	(0.075)	(0.125)	(0.018)
_cons	2.078*	2.188*	0.269	0.560*
	(1.027)	(1.028)	(0.171)	(0.245)
Observations	229	229	229	229
Adjusted R^2	0.161	0.190	0.039	-0.013

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Bootstrapping standard error is in parentheses.

Table B7: Quadratic relationship between depression and HPD

	HPD (75 − 100%)
$depression$	0.349***
	(0.132)
$depression\ squared$	-0.008*
	(0.003)
age	0.008
	(0.017)
$female$	-0.370
	(0.828)
$employed$	-0.446
	(1.113)
$college\ or\ bachelor$	-1.073
	(1.171)
$postgraduate\ or\ professional\ degree$	-1.640
	(1.391)
$single$	-0.561
	(0.858)
$income$	-0.042
	(0.075)
_cons	2.080*
	(1.027)
Observations	229
Adjusted R^2	-0.002

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Bootstrapping standard error is in parentheses.

Table B8: Mediation regression outputs from ex-post analysis

	Hypothesis 1 PG	**Hypothesis 2** PG	**Hypothesis 3** HPD
$depression$	0.101***	0.092**	0.149*
	(0.028)	(0.028)	(0.068)
HPD (75 − 100%)		0.064*	
		(0.033)	
age	-0.032	-0.031	-0.012
	(0.019)9	(0.018)	(0.046)
$female$	-0.396	-0.358	-0.599
	(0.427)	(0.423)	(1.048)
$employed$	0.035	0.041	-0.091
	(0.624)	(0.618)	(1.532)
$college\ or\ bachelor$	.243	0.378	-2.131
	(0.593)	(0.592)	(1.447)
$postgraduate\ or\ professional\ degree$	-0.302	-0.122	-2.840
	(0.676)	(0.676)	(1.648)
$single$	-0.335	-0.340	0.078
	(0.452)	(0.448)	(1.111)
$income$	-0.018	-0.023	0.091
	(0.082)	(0.081)	(0.202)
_cons	2.646*	2.941*	-4.684
	(1.163)	(1.163)	(2.857)
Observations	159	159	159
Adjusted R^2	0.074	0.090	-0.001

Note: * $p < 0.05$; *** $p < 0.001$. Bootstrapping standard error is in parentheses.