THE SEVERITY OF GAMBLING PROBLEM AND LOSS AVERSION IN HEALTHY GAMBLERS: THE IMPLICATIONS OF PROSPECT THEORY IN GAMBLING RESEARCH

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Abstract

Gambling decisions are inherently risky decisions involving wins and losses. The severity of gambling problems varies with the persistence of betting despite mounting losses. ‘Prospect Theory’, a descriptive model of risky decision-making from the field of behavioural economics, describes an influential phenomenon called Loss Aversion: the natural tendency for “losses to loom larger than gains” when people evaluate risky choices (Kahneman and Tversky, 1992). It is an intuitive prediction that people with the more severe gambling problem will display systematic alterations in their loss aversion. Experiment 1 reviewed two widely-used loss aversion tasks (the ‘matrix’ and ‘staircase’ methods) in the past studies, which also have varied in whether trial-by-trial outcome feedback was presented within each task. Hence, Experiment 1 was a methodological study. It aimed to evaluate whether the presentation of outcome feedback influences loss aversion scores with student samples, as a precursor for Experiment 2 using this procedure in regular gamblers. Experiment 2 recruited non-problem gamblers with varying levels of sub-clinical gambling problems. With the established task, it studied the relationships between the severity of gambling problems and risk preferences including risk attitudes across the gain and loss domains, loss aversion, and probability distortions. In Experiment 1, the outcome feedback did not show significant influence on the level of loss aversion. In Experiment 2, the findings indicated that the risk attitudes in the gain domain were the only Prospect Theory-based variable that correlated with the severity of gambling problems; participants with more severe problems tended to be more risk-seeking in the gain domain, and in the loss domain, all participants displayed ambivalent choices between risk-seeking and risk-averse. Moreover, the level of loss aversion and the magnitudes of probability distortions for potential gains and losses did not correlate with the severity of gambling problems.

Lay Summary

The severity of gambling problems lies on a continuum; many clinically healthy gamblers would share similar cognitions with pathological gamblers and experience negative consequences to some extent. Intuitively, the systematic changes in the risk preferences may assist the development and maintenance of gambling problems since gambling is inherently risk-seeking choices. This thesis aimed to explain the development of gambling problems in healthy gamblers through three potential mechanisms in respect to loss aversion, probability distortions, and risk attitudes for gains and losses. Understanding the mechanisms of the motivation would be insightful for the progression of gambling problems, as it distinguished the bigger contributing factors to gambling problems. By targeting the specific aspects of risk preferences, more effective methods might be developed to inhibit the further deterioration from a sub-clinical problem gambler to a pathological problem gambler.

Preface

I completed the experimental designs and data analysis for this thesis under the supervision of Dr. Luke Clark and Dr. Eve Limbrick-Oldfield. The data collection was completed with the help from the undergraduate research assistants: Jessica Cho, Natalie Cringle, and Candy Chua.

The Behavioural Research Ethics Board at the University of British Columbia approved Experiment 1 (H17-01856) and Experiment 2 (H16-01168). Informed consent was obtained from all participants upon their arrival.

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List of Symbols and Abbreviations

u	Basic utility function in the gain and loss domains
U	Utility function
α	Power of the utility function
α^{+}	Power of the utility function in the gain domain
α^{-}	Power of the utility function in the loss domain
δ	Decision weight
δ^{+}	Decision weight in the gain domain
δ^{-}	Decision weight in the loss domain
λ	Loss aversion coefficient
G	Gain
L	Loss
G^{*}	Certainty equivalent for a gain-only gamble
L^{*}	Certainty equivalent for a loss-only gamble
PT	Prospect Theory
EUT	Expected Utility Theory

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Chapter 1: Introduction

Gambling refers to the wagering of something valuable on an event with an uncertain outcome. The motivation of seeking uncertainty seems inherent in human nature. The earliest form of gambling can be dated to 4000 BC, and most cultures have had some form of gambling in human history (Schwartz, 2006). From the evolutionary perspective, the preference for uncertainty is essential in the survival mode. Humans may take risks to compensate for the unpredictability of lack of control (Anselme and Robinson, 2013), or to secure gains by engaging in wars, trade, work, and other risky activities (Ferentzy and Turner, 2013). Modern gambling is just a specific form of risk-taking that only involves rewards of wealth.

In modern gambling games (e.g., casino games, lotteries, sports betting, horse racing), money is the typical commodity for both the wagers and outcomes (BC Finance, 2014; Schüll, 2012). Most gamblers continue betting although they acknowledge that the odds of winning are designed to favour the commercialized gambling venues, and that gambling is expected to incur monetary losses in long run. Hence, gambling is a paradox in the neoclassical economics theories, such as the Rational Choice Theory and Expected Utility Theory. Those theories assume that decision-makers i) face a known set of alternatives, ii) take all available information into account in analyzing the costs and benefits of the choices, and iii) choose the option that maximizes expected utility, usually in the form of wealth (Bernoulli, 1754). The violation of financial rationality suggests that monetary rewards *per se* are not the sole motivator of gambling. Rather, biological, cognitive, and emotional factors may help to explain the perseverance of gambling behaviour (Zeelenberg and Pieters, 2004; Hodgins, Stea, and Grant, 2011; Shen, Fishbach, and Hsee, 2014).

For instance, classical choice theories (e.g., Expected Utility Theory; Bernoulli, 1954; Prospect Theory, Kahneman and Tversky, 1979) state that individuals are risk-averse, preferring certainty over uncertainty when facing potential gains. However, evidence from multiple disciplines suggested that individuals can prefer rewards from uncertain over safe options. On the neurochemical level, reward uncertainty magnifies the main neurotransmitter of motivation, mesolimbic dopamine (Preuschoff, Bossaerts, and Quartz, 2006; Ikemoto, Yang, and Tan, 2014). On the cognitive level, uncertain rewards stimulate higher and prolonged pleasure and arousal compared to certain rewards (Wilson, Centerbar, Kermer, and Gilbert, 2005), and these positive experiences (i.e., excitement and interest) boost the motivation of pursuing uncertainty (Shen et al., 2014). The study revealed that the preference for uncertainty occurs only when individuals focus on the process of pursuing reward, but not on the reward itself (Shen et al., 2014). Therefore, the scientific examination of gambling needs to be approached not only from the financial outcome of games, but also from the subjective experience of gamblers.

Commercialized gambling is a widespread form of entertainment. Canada started to legalize and expand gambling accessibility from the 1970s. Nowadays, lotteries, bingo, and horse racing are available in every province. Casinos, i.e. licensed premises that house slot machines, roulette, and skill-based forms of gambling like poker and blackjack, are available in most provinces (Ladouceur, 1996). The 2014 British Columbia gambling prevalence report found that 72.5% of British Columbians have gambled at least once in the past 12 months (BC Finance, 2014). Overall, the majority of gamblers played for entertainment and do not manifest any negative consequence. However, gambling may become excessive in a small proportion of gamblers, and dominate their lives with detrimental financial, social, and psychological consequences. In 2013, the fifth edition of the Diagnostic and Statistical Manual of Mental

Disorders (DSM-5) reclassified Pathological Gambling (now called Gambling Disorder), the extreme form of problem gambling, from the Impulse Control Disorders category to the only behavioural addiction. Individuals need to meet at least four of criteria (listed in Table 1) to be clinically diagnosed with Gambling Disorder (American Psychiatric Association, 2013).

DSM-5 Criteria of Gambling Disorder
1. Need to gamble with increasing amount of money to achieve the desired excitement
2. Restless or irritable when trying to cut down or stop gambling
3. Repeated unsuccessful efforts to control, cut back on or stop gambling
4. Frequent thoughts about gambling
5. Often gambling when feeling distressed
6. After losing money gambling, often returning to get even
7. Lying to conceal gambling activity
8. Jeopardizing or losing a significant relationship, job or educational/career opportunity because of gambling
9. Relying on others to help with money problems caused by gambling

Table 1. Diagnosis criteria for Gambling Disorder.

In addition, the severity of gambling problems lies on a continuum, and many gamblers still have sub-clinical symptoms that are termed ‘problem gambling’. Worldwide, 0.1% to 5.8% of individuals have gambling problems; in British Columbia, this estimate is 3.3%, with 0.7% meeting the criteria of likely Gambling Disorder (BC Finance, 2014; Calado, and Griffiths, 2016).

Economics and psychology provide two cornerstones for studying gambling, from complementary perspectives. Economists traditionally stand on the objectivist position, assuming gamblers’ sole motivation is to improve their wealth (Conlisk, 1993). Economics formalizes a theoretical framework of externally observable choices based on utility maximization and equilibrium (Royden, Suppes, and Walsh, 1959; Elster and Roemer, 1993). However, economics fails to recognize the anomalies in human subjective experience, such as willpower, self-interest, and rationality (Mullainathan and Thaler, 2000), and thus does not provide a good explanation of gambling with negative payoffs and increased risk. By contrast, psychology recognizes internal cognitive distortions and bias in the decision process. For example, the representativeness heuristic asserts that individuals tend to judge the likelihood of an event by comparing it to a prototype with a known likelihood (Tversky and Kahneman, 1974). Following this rule of thumb, gamblers may falsely over-estimate the probability of winning after consecutive lost bets in a game of chance, if they believe the event probability in the short-run resembles the probability in the long-run. The availability heuristic happens when individuals judge the likelihood of an event by the ease of recall (Tversky et al., 1974). For instance, gamblers would have higher expectation of winning if they observe others winning. While these mental short-cuts simplify strategies in decision-making, they may also falsely enhance gamblers' beliefs about winning (Fortune and Goodie, 2012). Additionally, psychology is more tolerant to the incorporation of hedonic experience into decision-making; for example, how emotions such as fear, regret, irritation, happiness, and anger may bias our choice processes. In the real-world case of the Dutch postcode lottery, a player's postcode is their ticket number. Hence, individuals would anticipate more regret if their neighbor wins the prize and they did not participate, compared to the traditional ticket-based lottery. The anticipated regret in the postcode lottery would consequentially encourage lottery purchases, despite the very low chances of winning (Zeelenberg et al., 2004). Incorporating with the more realistic assumptions about decision-makers' rationality, the structured economic models will be improved in the description and prediction of decision under uncertainty. Thus, an interdisciplinary field of decision-making called Behavioural Economics appeared.

Prospect Theory

One of the most influential contributions from Behavioural Economics is “Prospect Theory”. It is a descriptive economic model of decision making under risk with parametrized functions (Tversky and Kahneman, 1992). Risk is a special form of uncertainty where the probabilities of outcomes are known, whereas the traditional Knightian uncertainty applied to the situations where the probabilities are unknown (Brevers et al., 2012; Knight, 1921). Prospect Theory provides a natural theoretical framework to operationalize gambling decisions. It states that risk preference is jointly determined by the *Value Function*, which is the cognitive evaluation of outcomes, and the *Probability Weighting Function*, which is the subjective perception of the event likelihoods associated with respective outcomes (Figure 1). In contrast, the *Utility Function* solely determines risk preference in the traditional Expected Utility Theory, which does not consider the subjective probability.

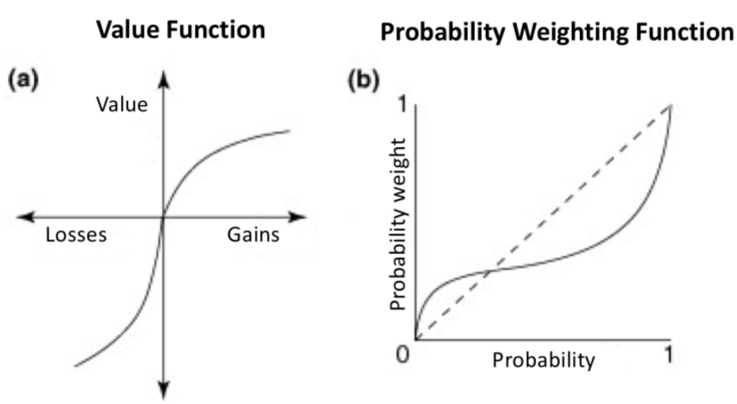

Figure 1. The value function and the probability weighting function in Prospect Theory.

The Value Function

The value function represents states of wealth over gains and losses relative to a reference point (i.e., current wealth) and defines the change of wealth. Tversky et al., (1992) asserted that the value function is an S-shape curve exhibiting diminishing marginal value. The concavity of the value function in the gain domain describes risk aversion when choosing between gains (i.e. a certain gain is preferred over a risky gain). On the other hand, the convexity of the value function in the loss domain describes risk seeking for decisions involving losses (i.e. a risky loss is preferred over a certain loss). The presentation of a choice can be manipulated by the salience of reference, leading an individual perceives the outcome either as a gain or loss and subsequently reversing their risk attitude (Kühberger, 1998). The reversal of risk preferences in the gain and loss domain is called the "Reflection effect".

Loss Aversion

The value function is steeper in the loss domain than the gain domain (Figure 1). This is a key property in Prospect Theory that accounts for the phenomenon of loss aversion, that individuals weight losses more than equivalent gains. The level of loss aversion seems naturally relevant to gambling behaviour, which reflects reduced aversion against negative consequences, such as monetary losses.

Loss aversion is commonly observed from decisions involving mixed (gain-loss) gambles that offers equal chances of winning or losing. For example, would you accept or reject a coin flip that offered winning $60 or losing $50? Many people would reject this gamble, despite the evident positive expected value; rejection implicates loss aversion because the loss of $50 is expected to cause more harm more than the pleasure from winning $60. Loss aversion scales with higher winning amounts required to compensate for the loss. The effect of loss aversion could also be observed from physiological data. The measurement of skin conductance responses (SCR) demonstrated that losses induce higher arousal than equivalent gains (Sokol-Hessner, Camerer, and Phelps, 2012). Functional magnetic resonance imaging studies (fMRI) found high behavioural loss aversion correlated with decreased activity in striatum and ventromedial prefrontal cortex (VMPFC) at decision (Sokol-Hessner et al., 2012; Tom, Fox, Trepel, and Poldrac, 2007) and increased activity in amygdala (De Martino, Camerer, and Adolphs, 2010) at feedback (Sokol-Hessner et al., 2012). Further, success in downregulating loss aversion corresponded to reduction in amygdala responses to losses but not to gains (Sokol-Hessner et al., 2012). The amygdala plays a mediator role across many contexts (Gläscher and Adolphs, 2003; McGaugh, 2004). Combining the previous evidence, the amygdala may mediate the level of loss aversion in responses to outcome feedback and pass it on to the striatum, the responses are manifested in behavioural loss aversion at decision ultimately (Sokol-Hessner et al., 2012). The neural correlates of amygdala implicated the association of emotion to loss aversion.

Loss aversion is quantifiable in a Prospect Theory based model. A loss aversion parameter, denoted as the lambda (λ) coefficient, is then a ratio between the utility of losses and utility of equivalent gains. When $\lambda = 1$, losses are valued equivalently to gains (i.e., “loss neutral”); when $\lambda > 1$, losses are over-valued compared to equivalent size of gains (i.e., “loss-averse”); when $\lambda < 1$, gains are over-valued than equivalent size of losses (i.e., “gain-seeking”). In past experimental work, healthy people typically weight losses twice as equivalent gains (Table 2).

Study	Feedback Condition	Median λ
Takeuchi et al., 2016	NA	3.74
Abdellaoui et al., 2008	NA	2.61
Kahneman et al., 1992	NA	2.25
Tom, Fox et al., 2007	No-feedback	1.93
Genauck et al., 2017	NA	1.89
Gelskov et al., 2016	No-feedback	1.82
Giorgetta et al., 2014	Feedback	1.25
Lorains et al., 2014	No-feedback	2.25
De Martino et al., 2010	Feedback	1.64

Table 2. Loss aversion coefficients of healthy participants in past studies, including control groups in studies of problem gamblers.

The Probability Weighting Function

The probability weighting function defines that the probability of an outcome is skewed by its attractiveness or importance. The function is an inverse-S shape curve (Tversky et al., 1992). Individuals tend to over-weight low probabilities and under-weight moderate to high probabilities.

Gambling and Loss Aversion

Individuals with gambling problems continue with their betting despite expected losses in the long-term. *Prima facie*, this tendency indicates a strong preference towards risk. Groups of participants with gambling problems show reliable impairments in decision-making under both risk and uncertainty, compared to healthy control groups (Brand et al., 2005; Brevers et al., 2012; Lawrence, Luty, Bogdan, Sahakian, and Clark, 2009; Ligneul, Sescousse, Barbalat, Domenech, and Dreher, 2013; Roca et al., 2008). For instance, in the Iowa Gambling Task (adapted from Bechara, Damasio, Damasio, and Anderson, 1994), participants were asked to choose from four decks of cards, in which two decks returned $100 of winning and $250 of losing at 50/50 (disadvantageous in long-term) and another two returned $50 of winning and $50 of losing at

50/50 (advantageous in long-term). The feedback was presented after each selection. The total number of trials was 100, and the outcomes and probabilities were not revealed to participants; thus, decision-making under uncertainty. Problem gamblers preferred disadvantageous decks and learnt slower from feedback compared to healthy control groups (Brand et al., 2005; Brevers et al., 2012), indicating impulsive behaviour towards high-uncertain rewards (Brevers, Bechara, Cleeremans, and Noël, 2013). In the coin flipping task (adapted from Tom, et al., 2017), participants were asked to accept or reject 50-50 mixed gambles. The sizes of potential gains ranged from 10 to 40 euros and potential losses ranged from 5 to 20 euros, in increments of 2 euros. A total number of 256 random gambles were completed. Even at this situation where explicit risk information was available, problem gamblers were more likely to accept the gambles throughout the task compared to the healthy control group (Brevers et al., 2012).

Elevated risk-taking behaviour can be driven by cognitive distortions, such as illusion of control and beliefs in luck as a magical force (Ladouceur and Walker, 1996). These distortions arise from the poor understanding of independence of chance events, and ultimately reduce estimation of risk and encourage excessive risk-seeking behaviour (Spurrier and Blaszczynski, 2014). Erroneous perceptions of probability are common during gambling, which typically involves low probabilities of winnings. A systematic probability distortion, such that over-weighting small winning probabilities, could make gambling more attractive (Kahneman et al., 1979). By extension, problem gamblers may exaggerate the over-weighting of small winning probabilities even more than the healthy population, manifesting in exaggerated upward skew of the probability weighting function at the small probabilities (Ligneul et al., 2013). Alternatively, problem gamblers may simply be more risk-seeking globally, and over-weight the winning probabilities over the whole probability range, manifesting in upward shift of the probability weighting function. The study by Ligneul et al., (2013) in fact supported this latter ‘elevation hypothesis’, but only tested probability processing in the gain domain. Because the current task assesses risk preference in the gain and loss domain with 50-50 gambles, it was possible to assess the probability distortions at 50% in the both domains.

Loss aversion is another key factor involved in risky decision. Because gambling is inherently associated with elevated risk taking despite mounting losses, it is intuitive that the standard over-sensitivity to losses over equivalent-size gains in healthy people may be attenuated in individuals with gambling problems, i.e. reduced loss aversion parameters. This hypothesis is supported by emotional signaling deficits in problem gamblers who exhibit equivalent anticipatory SCRs and heart rate responses between a choice with large potential gain and a choice with larger potential loss. By contrast, healthy controls show larger anticipatory SCRs and heart rate responses when considering choices with potential losses compared to those with only gains (Goudriaan, Oosterlaan, de Beurs, and van den Brink, 2006). According to the somatic marker hypothesis, unconscious bodily responses contribute to decision-making (Damasio, 1996). Hence, lower psychophysiological reactions to losses may lead to risky decision-making. On the other hand, a hallmark of problem gambling is “loss chasing”: continued betting in order to recover from losses (American Psychiatric Association, 2013; Campbell-Meiklejohn, Woolrich, Passingham, and Rogers, 2008). Neurological evidence from Positron Emission Tomography (PET) scanning shows increased dopamine release in ventral striatum in problem gamblers who are losing (Linnet, Peterson, Doudet, Gjedde, and Møller, 2010), indicating that problem gamblers desire more betting after losses. Chasing behaviour seems to implicate that individuals with gambling problems may be more reactive to losses than gains, compared to the healthy population. Supporting evidence was also found in analyses of online gambling data, that online gamblers who closed their accounts increased their bet sizes in the days leading up to account closure. This betting change was only on events with higher winning probabilities and could represent loss aversion during loss chasing (Xuan and Shaffer, 2009).

Crucially, recent studies have attempted to estimate loss aversion in people with gambling problems, using a case-control designs with behavioural economics measures. However, the findings are mixed. Takeuchi et al., (2016) found that the problem gamblers have similar level of loss aversion relative to the healthy control group (Takeuchi et al., 2016). While problem gamblers were more loss-averse than healthy control group in Giorgetta et al., (2014), the opposite direction was found as well (Gelskov, Madsen, Ramsøy, and Siebner, 2016; Genauck et al., 2017; Lorains et al., 2014). The study (Genauck et al., 2017) specifically measured luck/perseverance and illusion of control, the two typical beliefs that are associated with the severity of gambling problems (Raylu and Oei, 2002). Greater levels of these cognitive distortions were related to lower sensitivity to losses, implicating the higher severity of gambling problem, the lower sensitivity towards losses.

Problem gambling is a heterogeneous disorder; problem gamblers are classified by various personality traits, psychopathology, and gambling motivations (Milosevic and Ledgerwood, 2010), and gamblers may have problems with different gambling forms (Petry, 2003). Hence, heterogeneity of loss aversion may also exist within problem gamblers. In the study by Takeuchi et al., (2016), the problem gamblers scored at the two extremes of loss aversion (i.e., low, high) whereas the control group were mostly moderate. The heterogeneity in the problem gamblers was associated with clinical characteristics: problem gamblers with high craving intensity and excitement-seeking had low loss aversion, whereas problem gamblers with high anxiety showed elevated loss aversion scores, perhaps indicative of loss chasing tendencies

(Takeuchi et al., 2016). The heterogeneity was also related to the gambling forms. The problem gamblers who preferred non-strategic games (i.e., electronic gaming machines, bingo) demonstrated lower loss aversion relative to the healthy control group, whereas the strategic gamblers (i.e., poker, sport betting) were identical (Lorains et al., 2014). The non-strategic games, particularly slot machines, might induce greater gambling severity relative to the strategic games (Grant, Odlaug, Chamberlain, and Schreiber, 2012), so problem gambling severity may predict lower loss aversion.

The differences in loss aversion across those studies might due to various experimental methods and factors. For instance, the problem gamblers in the above studies have received varying amount of treatment as they recruited problem gamblers via different channels, such as gambling help centers or casino venues. As a result, the participants may react to losses differently. This treatment effect was supported by the evidence of systematic difference in loss aversion between problem gamblers at early and late stage of clinical treatment (Giorgetta et al., 2014). Specifically, compared to the healthy control group, the problem gamblers at the early stage had the similar level of loss aversion, but problem gamblers at the later stage had higher loss aversion.

The previous studies aimed to learn the difference of loss aversion between the problem gamblers and the healthy control group, and these mixed results encouraged the further study on loss aversion and gambling. But most of the previous studies (except Genauck et al., 2017) had not yet showed the direct correlation between loss aversion and the severity of problem gambling, which lies on a continuum. The current thesis specifically focuses on healthy gamblers, ranging from recreational, non-problem gamblers to gamblers with sub-clinical symptoms. Because even gamblers with low severity can be more similar to problem gamblers than healthy gamblers (Cox, Kwong, Michaud, and Enns, 2000), I would expect that the results from above problem gamblers might also applied to the sub-clinical problem gamblers. Overall, the current thesis aimed to answer how does loss aversion vary on the continuum of the severity of gambling problem in healthy population?

Loss Aversion and Feedback

Apart from the differences in above clinical and sample-related features, another critical difference was in the design choice of outcome feedback in those loss aversion tasks. Participants were asked to accept or reject a series of mixed gambles in all of above studies (Giorgetta et al., 2014; Gelskov, et al., 2016; Genauck et al., 2017; Lorains et al., 2014; Takeuchi et al., 2016), but only a portion of those studies presented outcome feedback after each decision (Table 2). The delivery of outcome feedback may alter the level of loss aversion for the following reasons. First, regulating 'perspective-taking' in decision-making could influence the level of loss aversion. Sokol-Hessner et al., (2009) asked the participants to make a series of gambles with two different evaluation strategies: 1) consider each gamble in isolation from each other, taking the short-term perspective; 2) consider each gamble as a part of a portfolio, taking the long-term perspective. The participants focused on the long-term return were less loss-averse than the participants from the short-term perspective, which resulted in higher sensitivity in recent losses. The manipulation of feedback frequency in repeated gambles (in contrast to one-shot gambles) would influence the degree of myopia, at which an individual takes a short-term perspective in decision-making (Benartzi and Thaler, 1995). Less frequent feedback delivers information at a more aggregate level, and frames decisions in long-term (Langer and Weber, 2008). Hence, the absence of feedback may resemble the portfolio condition and results in lower level of loss aversion than the presentation of feedback.

At the neural level, outcome feedback modulates activity in multiple regions including striatum, VMPFC, and amygdala; these are regions that also reflect loss aversion (De Martino et al., 2010; Sokol-Hessner et al., 2012; Tom et al., 2007). The mediating role of the amygdala in responses to outcome (Sokol-Hessner et al., 2012) suggests that loss aversion may be an emotional construct, such that individuals are averse to loss because it leads to negative emotion, such as fear (Camerer, 2005), and loss aversion is reduced (in fact abolished) in neurological patients with amygdala damage (De Martino et al., 2010). Because feedback elicits emotional responses to the outcomes including activity in the amygdala, a higher level of loss aversion is expected with the presentation of feedback compared to repeated choices without the feedback.

The above studies explain how experiencing outcomes can affect individuals' behaviour in a series of choices, but individuals may also obtain insights into the best strategy simply through repeated experience with choosing, in the absence of feedback. For instance, Ert and Erev (2013) found that their participants were loss-neutral during initial choices and became more loss-averse with time in repeated mixed gambles. This time effect was not due to a reaction to outcomes, because the task did not deliver feedback, hence it was interpreted as learning without feedback (Ert et al., 2013; Weber, 2003). To compensate for the absence of feedback, individuals may apply mathematical rules (i.e., expected value maximization) in the initial choices to guide their decisions under risk. Alternatively, they may simply use mental short-cuts (i.e., minimize the possibility of loss). Over repeated choices, if individuals found that the expected outcomes of accepting and rejecting the mixed gambles are similar (i.e., center closely around 0), that is both strategies would have little influence on the expected outcome, they may learn to adapt the simpler effort-saving loss aversion strategy (Brooks and Zank, 2005; Ert et al., 2013). Such situation may occur when the magnitudes of mixed gambles are small, and their expected outcome would be close to zero. Therefore, an individual can still learn from experience in the task environment even without feedback, but it is unclear how this learning weights the pattern of loss aversion compared to the effect of feedback. To summarize, the effect of outcome feedback on loss aversion measurement is ambiguous.

The current thesis consisted of two experiments. Experiment 1 used UBC undergraduates to study this methodological variable in the loss aversion task. It is critical to clarify the effect of feedback, which was a fundamental difference in the task design from the previous studies. Any difference between these conditions may explain the mixed results in the loss aversion studies comparing individuals with gambling problems against healthy control groups. The results from Experiment 1 then informed the choice of task for Experiment 2, which used a community sample of regular gamblers, and investigated the relationships between loss aversion, probability distortions, risk attitudes and the severity of gambling problems.

Chapter 2: Method review

Loss aversion is typically quantified by the loss/gain utility ratio. A standard procedure of utility measurement involves asking the individual to make a series of risky choices that each consist of a risky outcome and a riskless (certain) outcome. Utility is inferred from the point when an individual is indifferent (i.e. at chance) in accepting or rejecting the risky option. Because the loss aversion coefficient represents the direct comparison between the utility for gains and losses, the binary choices must include gains and losses (i.e., mixed gambles) simultaneously to measure loss aversion.

Under Prospect Theory, utility of gains and losses are modeled independently in a piece-wise function

$$U(x) = \begin{cases} u(x), & x \geq 0 \\ \lambda u(x), & x < 0, \end{cases} \qquad (1)$$

where u is the basic utility function that represents the intrinsic value of an outcome x. In empirical studies (Stott, 2006; Wakker, 2008), the utility function widely adopts a parametric specification, the power function $u(x) = x^{\alpha}$ for its simplicity and good fit. The α parameter is the function's curvature, indicating the diminishing sensitivity of utility to additional values. Typically, the utility function is concave for gains ($\alpha^{+} < 1$) and convex for losses ($\alpha^{-} < 1$). A smaller α represents an exponentially faster diminishing rate relative to a larger power (i.e., steeper slope). Along with the utility functions and loss aversion coefficient, utility is further weighted by the probability of an outcome. Contrasting with standard decision theory under the expected utility framework, where choices are valued in the probability-weighted utility, Prospect Theory states that a probability weighting function distorts the probability. Because gains and losses are valued independently, the function can assign different decision weights to each probability of gains δ^{+} and losses parameter δ^{-}.

Overall, the loss aversion coefficient is determined by combinations of utility curvatures and subjective decision weights in the gain and loss domains. Many choice models impose various assumptions on the parameters α^{+}, α^{-}, δ^{+}, δ^{-} to simplify the estimation of the loss aversion coefficient in the previous empirical studies. The following section reviews two common approaches and the corresponding models.

The Matrix Method

This widely-used procedure for estimating loss aversion is based upon a seminal fMRI study (Tom, et al., 2007), and has subsequently been used in several experiments in groups with problem gambling (Giorgetta et al., 2014; Gelskov et al., 2016; Genauck, et al., 2017; Lorains et al., 2014). The fMRI study (Tom et al., 2007) aimed to identify brain areas in which neural activity was enhanced for losses relative to equivalently-sized gains. Participants decided between a series of 50-50 mixed gambles (0.5, G; L) (i.e., 50% chance of winning $G and 50% chance of losing $L) against a certain zero outcomes. The gain amount and loss amount for the risky gamble were independently manipulated in order to discriminate the brain activities. To do this, each gamble was randomly chosen (without replacement) from a gain-loss matrix that ranged for gains from $10 to $40 (in $2 increments), and for losses from -$5 to -$20 (in $1 increments).

Tom et al., (2007) assumed linear utility functions where $\alpha^{+} = \alpha^{-} = 1$, as well as undistorted decision weights where $\delta^{+} = \delta^{-} = 0.5$. This was justified on the grounds that the magnitude of underweighting at 50% is small, $\delta \approx 0.45$ (e.g., Abdellaoui, Bleichrodt, and

L'Haridon, 2008; Prelec, 1998). The loss aversion parameter λ was estimated by fitting the participant's responses to the mixed gambles into a logistic linear regression:

$$Log\left[\frac{P(accept)}{1-P(accept)}\right] = \beta_{bias} + \beta_G G + \beta_L L, \qquad (2)$$

where the λ is the ratio of β_L and β_G, and β_{bias} is one's tendency to accept the gambles regardless of potential outcomes.

Sokol-Hessner et al. (2009) later developed a 3-parameter logistic model to fit the binary responses using non-linear utility functions. Their model estimated the expected value at which one was indifferent between accepting and rejecting the gamble with return of $0:

$$log[\frac{P(accept)}{1-P(accept)}] = (1 + exp\{-\mu * (U(0.5, G; L) - u(0))\})^{-1} \qquad (3)$$

$$U(0.5, G; L) = 0.5 * u(G) + 0.5 * \lambda * u(L) \qquad (4)$$

$$U(0.5, G; L) = 0.5 * G^{\alpha^+} + 0.5 * \lambda * L^{\alpha^-} \qquad (5)$$

where μ is the sensitivity of choice probability to gambles with the same estimated utility; μ = 0 indicating choices are random and independent from the gambles. The model assumed identical utility function for gains and losses at $\alpha^+ = \alpha^-$, as well as undistorted decision weights at 50%.

The Staircase Method

Although small, any distortion of probability perception may have impact on utility measurement and thus could influence the loss aversion coefficient. For instance, when $\delta^+ < 0.5$ (under-weighting), the utility of a risky choice (0.5, x; y) diminishes as $\delta^+[u(x) - x(\mathrm{y})] + u(\mathrm{y}) < 0.5[u(\mathrm{x}) - x(\mathrm{y})] + u(y)$; when $\delta^+ > 0.5$ (over-weighting), the utility of the risky choice increases as $\delta^+[u(x) - x(\mathrm{y})] + u(\mathrm{y}) > 0.5[u(\mathrm{x}) - x(\mathrm{y})] + u(y)$. The probability weighting thus influences the curvature of the utility function (Figure 2).

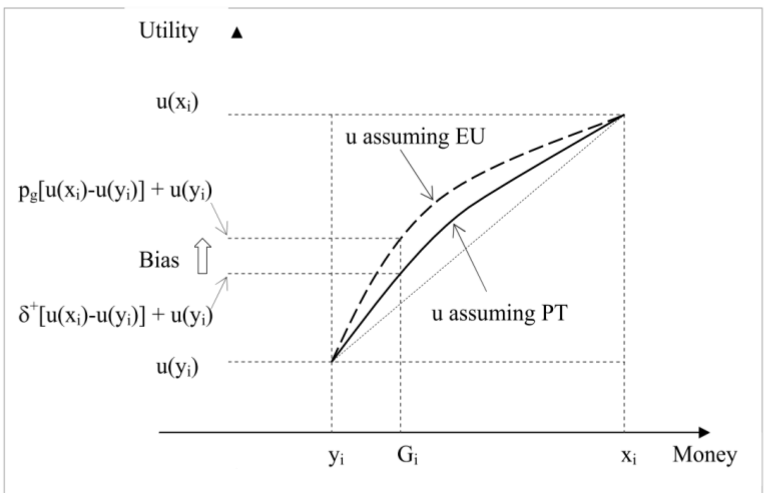

Figure 2. The effect of probability distortion on the utility function (Abdellaoui, et al., 2008).

Contrasting with an assumption of no probability weighting at 50%, Abdellaoui, et al. (2008) found that the weighting is small but significant, strengthening the necessity of a non-parametric probability weighting function to minimize the bias to the loss aversion coefficient. Abdellaoui et al., (2008) proposed a three-stage method, where the utility function curvatures and decision weights are initially estimated using pure gambles (i.e. stage 1: gains-only choices, stage 2: losses-only choices), and then at stage 3 the two utility functions were linked using mixed gambles to elicit loss aversion. This method employed a series of paired 50-50 risky and riskless choices to infer utility from the indifference points, at which the individual switches preferences and the value of the certainty option is psychologically equivalent to the risky option, and such value is so-called certainty equivalent. Only the probability weighting of 50% is estimable in this method. The behaviour at the risky gain-only and loss-only gambles reflects individuals risk attitudes in a single outcome valence, whereas the behaviour in the mixed domain reflects the level of loss aversion. For instance, the risk-taking behaviour indicate a risk-seeking attitude in the pure gambles and a level of loss aversion in the mixed gamble.

Stage 1: eliciting utility in the gain domain

Stage 1 comprises only pure gain gambles to measure utility in the gain domain. Participants were asked to choose between a risky option (0.5, x_i; y_i) and a riskless option G_i, for which $i = 1,2,3,4,5,6$. The value of G_i started at the expected value of the risky option and adjusted over successive 6 iterations to reach the indifference point of the two options. The adjustment followed the staircase procedure: if the participant chose the risky option, the amount of the guaranteed gain G_i increased in the next gamble; if the participant chose the riskless option, the amount of the guaranteed gain decreased in the next gamble. The step size was half of the change in the previous gamble. The iterations successively narrow the range of the certainty equivalent. The midpoint of G_i between 5th and 6th gamble was taken as the certainty equivalent, denoted as G_i^*, implying the observable utility of the risky option. The utility at the indifference point is

$$u(G_i^*) = \delta^+(u(x_i) - u(y_i)) + u(y_i) \qquad (6)$$

or

$$G_i^* = (\delta^+(x_i^{\alpha^+} - y_i^{\alpha^+}) + y_i^{\alpha^+})^{1/\alpha^+}. \qquad (7)$$

Six certainty equivalents were obtained from six different starting values for the risky options. These were used to estimate the parameters α^+ and δ^+ in the gain domain.

Stage 2: eliciting utility in the loss domain

Stage 2 consisted of pure loss gambles to measure utility in the loss domain. Participants were asked to choose between a risky option (0.5, x_i; y_i) and a riskless option G_i, for which $i = 1,2,3,4,5,6$. If the participant chose the risky option, the amount of guaranteed loss decreased in the next gamble; if the participant chose the riskless option, the amount of the guaranteed loss increased in the next gamble. The certainty equivalent L_i^* was obtained similarly as in the gain domain. The utility at the indifference point followed

$$u(L_i^*) = \delta^-(u(x_i) - u(y_i)) + u(y_i) \qquad (8)$$

or

$$L_i^* = (\delta^-(x_i^{\alpha^-} - y_i^{\alpha^-}) + y_i^{\alpha^-})^{1/\alpha^-}. \qquad (9)$$

Stage 3: assessing loss aversion

Stage 3 used mixed gambles to measure the loss aversion coefficient λ by directly comparing the utility of gains and losses. Their respective utility functions were linked by an indifference point between a mixed gamble $(0.5, G; L)$ and 0. The initial mixed gamble consisted of a gain G_i^*, a certainty equivalent in the stage 1, and an equivalent amount of loss $L = -G_i^*$. The amount of loss was adjusted successively in 6 iterations: if the participant chose the risky option, the amount of loss increased in the next gamble; if the participant chose the riskless option, the amount of loss decreased in the next gamble. Taking the options at the 6th gamble as the indifference point, the utility is

$$\delta^{+}u(G^{*}) + \delta^{-}\lambda u(L^{*}) = u(0) \qquad (10)$$

where G^{*} and L^{*} were the outcomes at the indifference. δ^{+}, δ^{-}, α^{+}, and α^{-} were known from the stage 1 and 2, λ could be calculated. Six λ values were derived from the six certainty equivalents, and I take the median as the individual's overall loss aversion coefficient.

In summary, measurement of the loss aversion coefficient requires locating the indifference points for mixed gambles against a riskless alternative. The matrix method estimates the indifference point in the logistic regression by asking participants to answer a large size of binary choices, including many trials for which that participant was far from their indifference point. The matrix method also involves repetition of gamble pairs that offer the same expected values. It is arguably inefficient to include such choices: inclusion of unnecessary trials makes the task longer and risks fatigue and de-motivation of the participant. At the same time, repetition of trials does offer a benefit of providing an internal check for a participant's consistency. By contrast, the staircase method establishes the indifference point more actively by adjusting the choices according to the participant's prior decisions, allowing the indifference point to reach more efficiently. However, within such paradigm, error propagation might occur with the "chaining" of old mistakes into new binary choices. Derivation of six indifference points reduces this concern, as the consistency across the indifference points can be checked. In terms of the model assumptions, the matrix method simplified the models and assumed 1) identical curvature in utility functions for gains and losses; 2) no probability weighting. By contrast, the staircase model was non-parametric and thus the estimated loss aversion coefficient was less likely to be confounded by assumptions, but it was potentially more susceptible to response error.

Chapter 3: Experiment 1

The outcome feedback had ambiguous effect on the level of loss aversion. Since feedback allows frequent outcome evaluation and enhanced emotional salience, participants in a Feedback condition may display myopic thinking and higher loss-averse than the participants in a No-feedback condition. But other factors, such as the potential learning without feedback may lead to an unknown direction. This led to the first hypothesis:

- *Hypothesis 1: Loss aversion will differ between the Feedback condition where trial-by-trial outcomes are presented, and the No-feedback condition where the trial-by-trial outcomes are unknown to participants.*

Methods

Participants

I recruited 85 healthy volunteers (37 male, age 19) from the undergraduate population at the University of British Columbia via the Human Subject Pool in the Department of Psychology. Only 2% of participants reported a gambling history in the last 12 months. The Problem Gambling Severity Index (PGSI; Ferris and Wynne, 2001) was administered to pre-screen potential gambling problems. The PGSI is a widely-used nine items scale measuring the severity of gambling problem, and it has good validity in distinguishing subgroups of gamblers in the general population. The scale has four response categories: “never”, “sometimes”, “most of time”, and “almost always”, scoring 0, 1, 2, and 3 respectively. It pertains to gambling activity over the past 12 months, and a total score of 0 indicates non-problem gamblers; 1-2, low-severity gamblers; 3-7, moderate-severity gamblers; 8-27, problem gamblers.

In the current study, no participants were classified as a problem gambler (score > 7), with 96% scoring 0. The study was approved by the Behavioural Research Ethics Board at the

University of British Columbia, and informed consent was obtained from all participants upon their arrival.

As a financial incentive, participants were told that their actual decisions on three randomly selected choices would be chosen and awarded as a cash bonus at the end of the experiment. Participants additionally received fixed course credit for their participation. No endowment was given on the loss aversion task. Participants were randomly assigned to the Feedback (n = 45) and No-feedback (n = 40) conditions.

The data analysis excluded choices that had a response time under 500 milliseconds or derived a loss aversion coefficient over 50. By these criteria, two participants were excluded.

Loss Aversion Task

The task consisted of 229 binary choices, arranged in two blocks: a staircase block and a matrix block, with a break between the two blocks. The order of the two blocks was fixed (staircase then matrix) as some values derived from the staircase choices were used to specify the matrix parameters. The choices were presented via a computerized task, with no imposed time limit for decisions. In the Feedback condition, wins were accompanied by a photo of coin stack presented on the screen along with an auditory chime, and losses were signified by a coin stack overlaid with a red cross, delivered with an aversive auditory stimulus. Feedback was presented for 2 seconds. The height of the coin stack varied proportionately with the magnitude of outcomes. In the No-feedback condition, a blank screen was presented for the same duration as the feedback in the Feedback condition, so that the trials lasted an equivalent duration. Each binary choice comprised a risky option with 50-50 probability of two outcomes, against a riskless (certain) option with a single value. The risky option displayed the potential outcomes in the two segments, and the riskless option was displayed in a full circle. Participants were instructed that there were no correct or wrong answers and no time limit for making decisions. The task started with three practice choices.

I. The Staircase Method

The task followed the method by Abdellaoui et al. (2008). Participants were first presented with a series of 50-50 binary choice questions, choosing between a risky and a riskless outcome. Six questions involved pure gains and six questions were pure losses. Each binary choice question iterated over six gambles, whereby the riskless option was adjusted based on participants' previous choice. The six iterations thus established an indifference point between the riskless and risky option. The method used six binary choice questions with increasing expected values to elicit six certainty equivalents and estimated the utility functions in the gain and loss domains respectively (Table 3). The total twelve binary choice questions were ordered randomly in the task.

	Q1	Q2	Q3	Q4	Q5	Q6
$\lvert x_i \rvert$	5	10	15	30	30	30
$\lvert y_i \rvert$	0	0	0	0	15	21

Table 3. The binary choice questions asked to elicited certainty equivalents for the utility functions.

After the pure gambles, participants were asked to choose between six 50-50 mixed gambles. In these trials, the initial gain and loss values of the risky option started at the certainty equivalents from the pure gambles, and each set of starting values again underwent six iterations to establish indifference points. In this way, the task estimated six loss aversion coefficients from the six mixed gambles. The median of the rest of loss aversion coefficients represented individual level of loss aversion.

II. The Matrix Method

In this block of the task, the binary choices only contained mixed gambles. Each gamble was uniquely and randomly selected from an 11 x 11 matrix of potential gains and losses. This matrix was individually generated using the certainty equivalents from the pure gambles in the staircase block. The gains ranged from the minimum to the maximum certainty equivalent from pure gain gambles; similarly, the losses ranged from the minimum to the maximum certainty equivalent from the pure loss gambles. In actual terms, the potential outcomes ranged from 0 to ± 30, and the distributions of gains and losses consisted of 11 equal steps in their ranges.

Participants' responses in the mixed gambles were fitted to the logistic linear regression, and the loss aversion coefficient was calculated as the β_{Gains} /β_{Losses} ratio. The exclusion criteria were 1) choices with response time under 500 milliseconds; 2) participants with a λ > 50 or a negative λ, which implied the failure of task comprehension as the probability of gamble acceptance decreased with increasing expected values. I excluded two participants, one with a short response time and one with a negative λ.

Results

The Staircase Method

I. Model Alternatives and Selection

The choices in pure gain (loss) gambles were used to estimate the power of the utility function α^+ (α^-) and the decision weight δ^+ (δ^-) in the non-linear regression (equation 10, 13). The loss aversion coefficient λ was then estimated in mixed gambles with known α and δ. I tested three alternative models: 1) a linear utility model, which assumed $\alpha^+ = \alpha^- = 1$; 2) a no probability weighting model, which assumed $\delta^+ = \delta^- = 0.5$; 3) the full model, which imposed no assumptions on the parameters α^{+}, α^{-}, δ^{+}, δ^{-}. These assumptions of linear utility and/or no probability weighting have been adopted in past literature estimating loss aversion (Tom et al., 2007; Sokol-Hessner et al., 2012; De Martino et al., 2010).

The full model offered the greatest mean adjusted R^2 (see Table 4) and was thus used for the statistical comparisons of the feedback conditions.

	Feedback	*Linear utility model*	*No probability weighting model*	*Full model*
Mean adjusted R^2	Gain	0.979	0.977	0.986
	Loss	0.986	0.983	0.991
	No-feedback			
Mean adjusted R^2	Gain	0.976	0.974	0.981
	Loss	0.977	0.978	0.983

Table 4. Experiment 1: Mean adjusted R-squared in the three staircase models. The model scored highest was identified as the best-fit model.

II. Loss Aversion

Each participant had six λ values that were estimated from the certainty equivalents of six pure gain binary choices, which had different level of expected magnitudes and might lead to different level of loss aversion. The non-parametric repeated measures ANOVA (Skillings-Mack test) was used for such magnitude effect. Table 5 shows the median λ from the six binary choice questions, and there was no significant difference in the λ values depending on which pure gain binary choices they were derived from, both in the Feedback, $x^2(5) = 1.67$, $p = .90$, and the No-feedback conditions, $x^2(5) = 3.70$, $p = .60$.

Feedback	G1	G2	G3	G4	G5	G6
Median λ	1.06	0.92	1.04	0.80	0.72	0.58
IQR	0.48- 3.30	0.40-2.00	0.35-2.42	0.19-2.82	0.11-3.07	0.10-3.52
No-feedback	G1	G2	G3	G4	G5	G6
Median λ	1.09	1.28	1.15	1.60	1.14	0.94
IQR	0.70-2.67	0.65-2.66	0.43-3.12	0.27-4.95	0.09-4.32	0.06-5.39

Table 5. Experiment 1: Median λ and Interquartile range (IQR) in the 6 mixed gamble questions.

Based on this consistency, I pooled the six questions and used the median λ to represent each individual's loss aversion estimate. The median λ was 1.06 (IQR = 0.23 – 3.44) in the Feedback condition, and 1.46 (IQR = 0.40 – 4.40) in the No-feedback condition. These λ values were not significantly different between the Feedback and No-feedback conditions[1], U = 757, p = .35. Collapsing across the two conditions, the pooled median λ was 1.22 (IQR = 0.33 – 4.10), which was significantly higher than 1 (reflecting loss-neutral choice), Z = 2.94, p < 0.01. However, loss aversion was not exclusively the dominant pattern among participants; there were 47 loss-averse ($\lambda > 1$) and 36 gain-seeking ($\lambda < 1$) participants (Figure 3), and the proportion of loss-averse participants was not significantly larger than the proportion of gain-seeking participants, $x^2(1)$ = 1.20, p = .27.

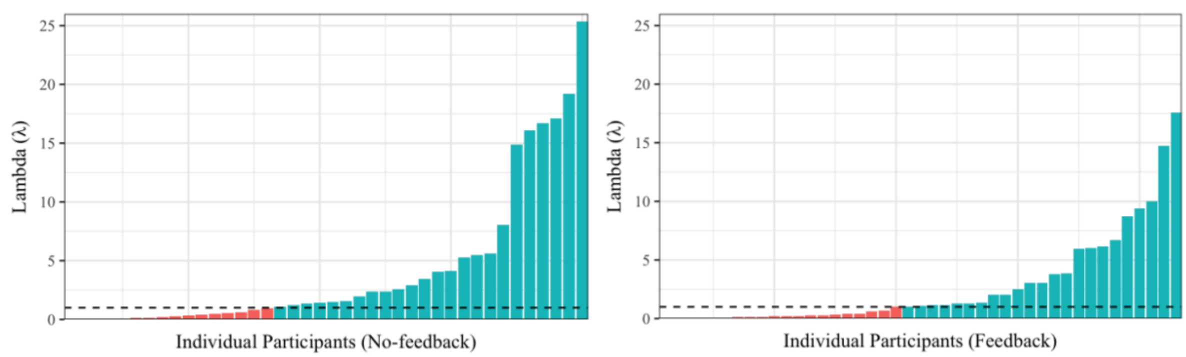

Figure 3. Loss aversion coefficients in the Feedback and No-feedback conditions from the staircase method. Blue bars indicate participants > 1.

Without modeling the decision weight δ and the utility curvature α, the level of loss aversion could be estimated roughly from the indifference points for the mixed gambles. Assuming δ = 0.5 and α = 1, a greater magnitude of gain relative to the corresponding loss is consistent with loss aversion. A larger *gain/loss ratio* reflects higher loss aversion. The

[1] Instead of removing λ > 50, winsorizing was also used to limit outliers. Loss aversion did not significantly differ between the Feedback and No-feedback conditions.

correlation between this *gain/loss ratio* coefficient and the modeled λ was estimated by a mixed-effect model, nested within participants. Significant, albeit moderate, correlations were observed in both the Feedback condition, $rho(41) = .34$, $p < .0001$, and the No-feedback condition, $rho(38) = .41$, $p < .0001$, showing consistency between the modeled λ and the raw participant choices.

III. Utility Function

In the gain domain, the median utility power estimators did not differ between the Feedback (median $\alpha^+ = .99$) and No-feedback (median $\alpha^+ = 1.23$) conditions ($U = 672$, $p = .09$). Similarly, in the loss domain, the median utility power estimators did not differ between the Feedback (median $\alpha^- = 1.35$) and No-feedback (median $\alpha^- = 1.12$) conditions ($U = 981$, $p = .27$). Collapsing the power estimators across the two conditions, the values were significantly higher than 1 (a linear utility function) in the gain domain (median $\alpha^+ = 1.14$, $Z = 3.07$, $p < .01$) and the loss domain (median $\alpha^- = 1.21$, $Z = 4.65$, $p < .0001$). In Prospect Theory, Tversky et al., (1992) estimated the concave gain and convex loss functions with powers of 0.88 in both domains, thus it is notable that the utility functions in my experiment were reversed, indicating *convex* gain and *concave* loss functions. As seen for λ values, these power estimators showed substantial individual differences based on their interquartile ranges (Table 6).

	α^+	α^+	δ^+	δ^-	λ
Median	1.14	1.21	0.4	0.34	1.22
IQR	0.81-1.81	0.97-2.03	0.24-0.50	0.21-0.49	0.24-3.99

Table 6. Experiment 1: Median model estimators in the staircase method.

In the gain domain, 60% of participants displayed a convex utility function (Table 7); this was significantly higher than the proportions with concave or linear functions, $x^2(2) = 45.5$, $p < .0001$. In the loss domain, 70% of participants displayed a concave utility function, which was also significantly higher than the proportion with convex or linear functions, $x^2(2) = 57.86$, $p < .0001$.

		Loss			
		Concave	Convex	Linear	Total
Gain	Concave	26	5	1	32
	Convex	32	18	0	50
	Linear	0	0	1	1
	Total	58	23	2	83

Table 7. Experiment 1: Classification of convexity of utility functions.

IV. Probability Weighting

In the gain domain, the median decision weight estimators (derived for probability of 0.5) did not differ between the Feedback (median $\delta^+ = 0.44$) and No-feedback (median $\delta^+ = 0.35$) conditions ($U = 1057$, $p = .07$). Similarly, in the loss domain, the median estimators did not differ significantly between the Feedback (median $\delta^- = 0.32$) and No-feedback (median $\delta^- = 0.38$) condition ($U = 705$, $p = .16$). Collapsing the two conditions together, a subjective probability of 0.5 was significantly under-weighted to $\delta^+ = 0.40$ in the gain domain ($Z = -4.23$, $p < .0001$) and $\delta^- = 0.34$ for losses ($Z = -5.83$, $p < .0001$). This degree of under-weighting was similar for gains and losses ($Z = 1.26$, $p = .21$). In Prospect theory (Kahneman and Tversky, 1992), the probability weighting function also under-weights probabilities of 0.5 in both the gain ($\delta^+ = 0.42$) and the loss ($\delta^- = 0.45$) domains.

The probability weighting was the main factor driving the curvatures of the utility functions. When the model assumed no probability distortion, the power estimators of the utility functions did not significantly differ from 1 in the gain (median $\alpha^+ = 0.85$, $U = 1382$, $p = .10$), and the loss domains (median α^{-} = 0.87, U = 1521, p = .31), and the curvature convexities were consistent with Prospect Theory.

The Matrix Method

The λ did not differ between the Feedback (median λ = 1.19, IQR = 0.84 – 1.88) and No-feedback (median λ = 1.38, IQR = 1 – 1.93) conditions (U = 736, Z = -1.13, p = .26) (Figure 4).

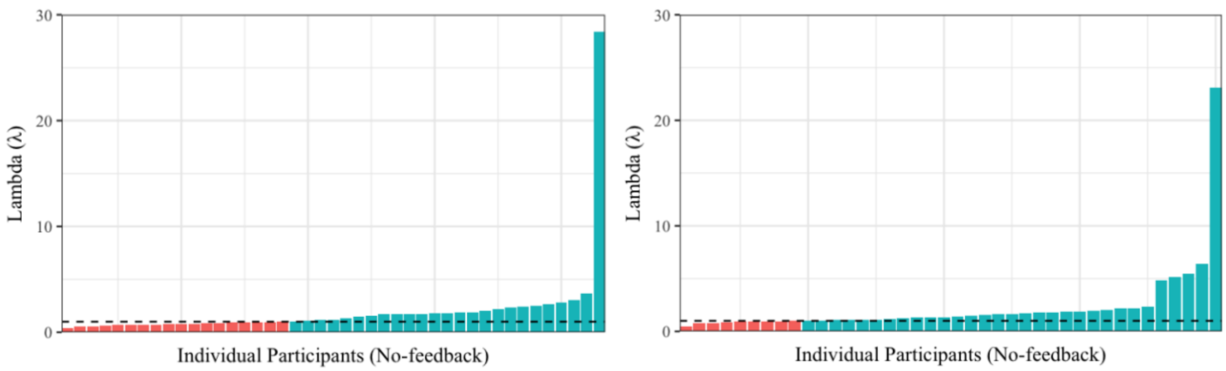

Figure 4. Loss aversion coefficients in the Feedback and No-feedback conditions from the matrix method.

The median of the pooled λ values across the two conditions was 1.33 (IQR = 0.94 – 1.91); again, this is significantly higher than 1, Z = 5.05, p < .0001, consistent with loss aversion. There were 56 loss-averse and 27 gain-seeking participants overall, and the proportion of loss averse participants exceeded the proportion of gain-seeking participants, $x^2(1)$ = 9.45, p < .01, such that loss aversion was the dominant bias.

No status-quo bias was observed. When controlling for the magnitude of gambles, participants did not have strong tendency to accept or reject the mixed gambles in the Feedback (β_{Bias} = -.60, p = .30) or the No-feedback (β_{Bias}= -.56, p = .54) conditions (Table 8).

Predictors	$\beta(SE)_{Feedback}$	p	$\beta(SE)_{No-Feedback}$	p
Gain	0.27(0.06)	< .001	0.33(0.10)	< .001
Loss	0.37(0.08)	< .0001	0.57(0.14)	< .001
Bias	-0.60(0.82)	0.3	-0.56(1.03)	0.54

Table 8. Experiment 1: Median coefficients of the matrix method.

Matrix vs. Staircase

As the matrix and staircase methods were designed to measure participants' level of loss aversion in mixed gambles, I expected stable choice patterns to be observed, with correlated λ values from the two methods. The level of loss aversion was moderately correlated between the matrix λ and the staircase *gain/loss ratio*, *rho*(80) = .65, p < .0001; notably, these two coefficients rely on the same assumptions of $\delta^{+} = \delta^{-} = 0.5$ and $\alpha^{+} = \alpha^{-} = 1$. The correlation was weakened when utility and probability weighting parameters were allowed to vary in the staircase, inconsistent with the matrix model. The matrix λ was not significantly correlated with the staircase Full model λ, *rho*(80) = .04, p = .73, which estimated under the non-parametric probability weights and utility powers. By controlling for the decision weights (δ^{+}, δ^{-}) in the staircase Full model in a partial correlation, their relationship remained weak, *rho*(78) = .03, p = .78. But when controlling for the utility powers (α^{+}, α^{-}) in the staircase Full model, a significant partial correlation with the matrix λ was observed, *rho*(78) = .30, p = .01. The correlation remained significant when controlling decision weights and utility powers simultaneously, *rho*(76) = .35, p < .01. The staircase model allowed utility and probability weighting parameters to vary, whereas the matrix model did not, and such differences resulted in the inconsistent level of loss aversion. Particularly, the parametric assumption of linear utility function caused the matrix λ to significantly deviate from the staircase λ, and the correlation between the two measurement methods increased when both models applied the same assumptions, particularly regarding the utility powers.

Discussion

The aim of this study was to test whether the presentation of outcome feedback affected loss aversion. The frequent evaluation of outcomes might encourage an individual to be myopic in the evaluation of repeated gambles, and more sensitive to losses in risky decisions (Benartzi et al., 1995). Further, induced emotion at feedback would mediate loss aversion (Sokol-Hessner et al., 2012). A learning effect without feedback might also happen with the gamble experience and influence the risky choices (Ert et al., 2013). However, past research has not explored whether loss aversion is affected by feedback, by directly manipulating the delivery of feedback. Past studies had conflicting results about the difference of loss aversion in problem gamblers and healthy controls (Giorgetta et al., 2014; Gelskov et al., 2016; Genauck et al., 2017; Lorains et al., 2014; Takeuchi et al., 2016). Importantly, their loss aversion tasks had the inconsistent design of feedback delivery, which might lead to the mixed results.

Although participants in the Feedback condition scored higher in loss aversion than the No-feedback condition, the presentation of feedback did not significantly impact participants' risky choices in the mixed gambles. That is, the level of loss aversion was similar in the Feedback and the No-feedback conditions. The experiment used two common loss aversion tasks, and the same pattern of loss aversion coefficients was found across the matrix and staircase methods, suggesting some robustness of the findings. Consistent with Prospect Theory, participants were overall loss-averse with the loss aversion coefficients above 1. However, the coefficients derived from the matrix and staircase methods in the current study were consistently smaller than many past studies used the same methods in healthy participants (Table 2), indicating participants in the current study preferred more of the risky option in the mixed gambles.

Loss aversion is known to show some magnitude dependency: small monetary gains and losses are expected to have small utility, and the pain of small losses is likely to be closer to the pleasure of equivalent gains (Harinck, Van Dijk, Van Beest, and Mersmann, 2007; Mukherjee, Sahay, Pammi, and Srinivasan., 2017). Thus, the low overall levels of loss aversion in the current study might due to the small monetary values at stake, with gambles having a maximum of $30. In Abdellaoui et al., (2008), participants displayed higher loss aversion when deciding with potential outcomes up to 10,000 euros (approx. CAD $15,000), or 15,000 yen (approx. CAD $175) in Takeuchi et al., (2016). It is possible that the small magnitudes made trivial emotional changes, especially the expected emotional reactivity of losses. Thus, a minimal change was reflected in the behavioural loss aversion under the Feedback condition, and subsequently, no significant difference was observed between the Feedback and No-feedback conditions.

Less frequent feedback led to long-term thinking and more frequent evaluation led to short-term thinking for the repeated choices; the delivery of feedback would change the choice strategy for risky choices. But there was no evidence of distinct perspectives and choice strategy between conditions. The extensive number of choices in the task was speculated to encourage participants to consider each gamble as within a big portfolio in the long-term regardless of feedback.

Participants did show larger loss aversion coefficients in the No-feedback condition across the matrix and staircase loss aversion tasks, although the difference was not statistically significant. Because of the robust pattern from both measurements, Experiment 2 in the community gamblers employed the No-feedback version of the task, because I reasoned that larger coefficients could increase the sensitivity of the task to individual differences. There would be many tied ranks of loss aversion if participants scored too closely, which would make it difficult to relate loss aversion to the severity of gambling problems in Experiment 2. Furthermore, the median loss aversion coefficients in the No-feedback condition was more consistent with findings in the past literature (Table 2). The second task modification for Experiment 2 concerned the staircase method, which adjusted gambles actively to locate the indifference points. But in Experiment 1, the size of the steps diminished quickly due to the small monetary magnitudes, so that the indifference points converged well before the sixth iteration. So, I reduced the number of iterations in Experiment 2 to increase the task efficiency.

Chapter 4: Experiment 2

The aim of Experiment 2 was to assess risk attitudes in regular gamblers recruited through the community, with varying levels of gambling problems. This study investigated the relationship between the severity of gambling problems and loss aversion, probability distortions, and risk attitudes.

First, because of the inherent association between gambling and risk-taking behaviour in losses, loss aversion was expected to be negatively correlated with the severity of gambling problems. On the other hand, other research suggested that loss chasing might be motivated by the higher sensitivity towards losses, which suggests an effect in the opposite direction. This led to the second hypothesis:

- *Hypothesis 2: loss aversion is correlated with the severity of gambling problem in healthy gamblers.*

The elevation hypothesis predicts a global over-weighting for the winning probabilities in problem gamblers, and thus the perceived gain probability at 50% was expected to positively correlate with the severity of gambling problem. Although the elevation hypothesis did not describe the probability weighting function in the loss domain initially (Ligneul et al., 2013), following the same logic of lowered risk estimation, loss probabilities were expected to be under-weighted globally. It suggested a negative correlation between perceived probability at 50% and the severity of gambling. However, because the probability weighting function has limited distortion at central probabilities around 50%, any correlations might be weak. Overall, the third hypothesis about the probability weighting was:

- *Hypothesis 3: the degree of probability distortion for the 50% probability correlates with the severity of gambling problem in healthy gamblers.*

Finally, the general population is risk-averse for gains and risk-seeking for losses, termed the reflection effect (Baucells and Villasís, 2010; Kahneman et al., 1979; Schoemaker, 1990). Because of the evident risk-taking behaviour in persistent gamblers, the reflection effect might not stand in individuals with gambling problems. Thus, this led to:

- *Hypothesis 4: gamblers with more severe gambling problems would more risk-seeking globally in the gain and loss domains.*

Methods

Participants

Community gamblers (n = 48; 23 men, mean age 48) were recruited to participate in a laboratory session. The inclusion criteria required that participants: 1) had played a slot machine at least once during past three months; 2) were not classified as a problem gambler. The PGSI (Ferris et al., 2001) was administered to evaluate problem gambling severity, individuals scored above 7 were excluded. I categorized participants further into three groups based on their PGSI scores, and the number of participants was balanced between groups: 14 non-problem gamblers (PGSI score = 0), 17 low-severity gamblers (PGSI score = 1 – 2), and 17 moderate-severity gamblers (PGSI score = 3 – 6; Figure 5).

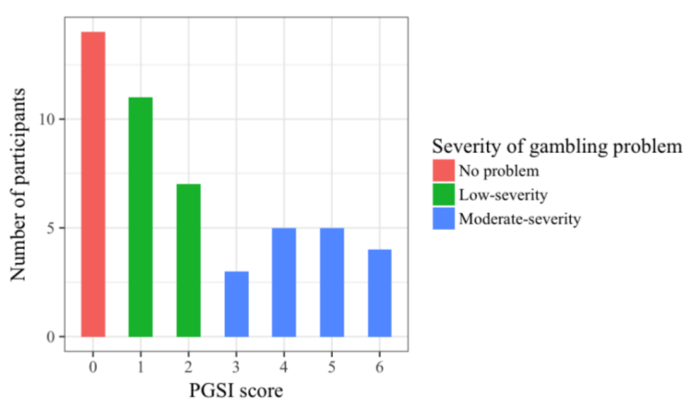

Figure 5. PGSI scores across groups of gambling severity

This experiment was part of a project which involved authentic slot machine play, hence I excluded problem gamblers due to ethical considerations around treatment seeking and risk of relapse. A parallel aim of this project was to investigate the house-money effect on gambling, by manipulating the endowment in two conditions: 1) an earning condition where participants initially earned the $40 endowment for both tasks in this project, i.e. the slot machine session and the loss aversion task; 2) a windfall condition where participants were given the $40 without any cost or effort.

At the beginning of the testing session, the participant was randomly assigned to either the earning condition (n = 24) or the windfall condition (n = 24). The participants in the earning condition incrementally earned the $40 by completing the Navon task (Navon, 1977), an attention-demanding task. On each trial, the participant was presented a Navon figure consisting of a larger global letter (S or H), which was composed by a different smaller local letter (S or H) on the monitor. The participant was asked to identify the local letter by keyboard press within 500 milliseconds. Each accurate respond was awarded 10 cents, with the task continuing until they had earned $40 cumulatively. Participants in the windfall condition were given $40 after reading magazines for 15 minutes. All participants were asked to put the cash into their wallet immediately after the $40 was given. The loss aversion task followed a slot machine session which was not the for the purpose of this current experiment. The net outcome from three randomly selected choices in the loss aversion task was awarded as part of the cash bonus at completion.

Loss Aversion Task

Similar to Experiment 1, the staircase method used the same 12 binary choice questions, but each choice only iterated 3 times to elicit the certainty equivalent. The matrix method consisted of the identical 11×11 matrix to Experiment 1. Participants made 175 binary choices in total.

The exclusion criteria were the same as in the Experiment 1. In the staircase method, one low-severity participant in the windfall condition was excluded due to large λ values from all six binary choice questions. In the matrix method, I failed to collect data from 3 participants (3 non-problem gamblers) in the earning condition and 4 participants (2 non-problem gamblers, 2 moderate-severity gamblers) in the windfall condition, due to the computer malfunction. In the end, 41 participants completed the matrix task and no participant was excluded.

Results

The Staircase Method

I. Model Alternatives and Selection

I ran the same three alternative models as in Experiment 1. Since the Full model had the largest mean adjusted R^2 in the regressions in the pure gain and the pure loss gambles (Table 9), α^+, α^-, δ^+, δ^- were estimated in calculating the individual λ values.

		Linear utility model	*No probability weighting model*	*Full model*
Mean adjusted R^2	Gain	0.975	0.97	0.983
	Loss	0.978	0.976	0.985

Table 9. Experiment 2: Mean adjusted R-squared in the three staircase models.

II. Loss Aversion

Table 10 shows the median λ elicited from each of the 6 binary choice questions.

	G1	G2	G3	G4	G5	G6
Median λ	0.84	0.94	0.86	0.65	0.58	0.43
IQR	0.24-2.21	0.17-2.08	0.23-2.02	0.02-1.79	0.01-1.44	0.00-2.79

Table 10. Experiment 2: Median λ and IQR of the 6 mixed gamble questions.

Again, the median λ was used to represent individual loss aversion because there were no significant variations in the λ values between the 6 questions, $x^2(5) = 3.69$, $p = 0.58$. Furthermore, the λ values were not significantly different between the earning (median $\lambda = 0.69$) and the windfall (median $\lambda = 0.82$) conditions ($U = 259$, $p = .73$). Thus, I pooled the λ values together for the following analysis.

Overall, the median λ was 0.80 (IQR = 0.1 – 2.17) which did not differ significantly from 1 as loss neutral ($Z = .47$, $p = .64$). The distribution of λ is shown in Figure 6. Loss aversion was not the dominant pattern of choices; there were 27 loss-averse and 20 gain-seeking participants, and their proportions did not significantly differ from each other, $x^2(2) = .77$, $p = .38$.

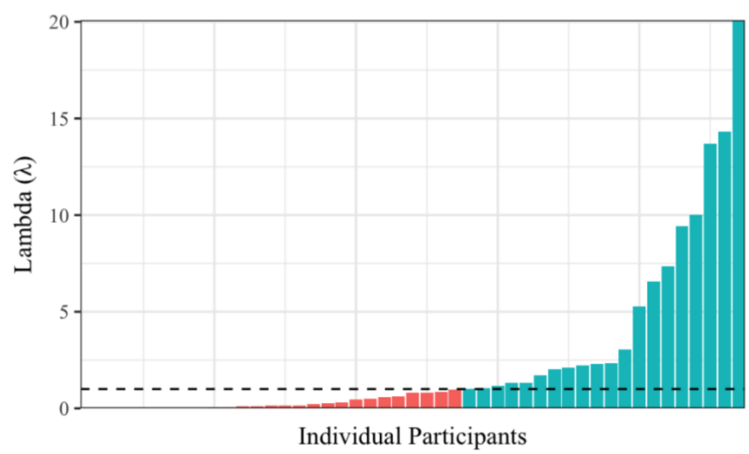

Figure 6. Loss aversion coefficients of community gamblers in the staircase method.

The modeled λ was significantly correlated with the $gain/loss\ ratio$ at the indifference points, *rho*(45) = .59, *p* < .0001, supporting the validity of the model.

III. Utility Function

In the gain domain, the median utility power estimator was 1.00, which did not significantly differ from a linear curvature (U = 638, p = .31). In the loss domain, the median utility power estimator was 1.42, which was significantly higher than 1 (U = 876, p < .0001), reflecting a concave loss function. Overall, the power estimators had considerable variation between individuals, based on the interquartile range (Table 11). The concave function was the dominant pattern for both gains (47%) and losses (62%), which were significantly higher than the proportions of the convex and linear functions in the gain domain, $x^2(2)$ = 11.02, p < .01, and the loss domain, $x^2(2)$ = 17.02, p < .001 (Table 12).

	α^+	α^+	δ^+	δ^+	λ
Median	1.00	1.42	0.38	0.37	0.80
IQR	0.75-1.79	1.00-2.70	0.17-0.65	0.16-0.48	0.10-2.17

Table 11. Experiment 2: The median model estimators in the staircase method.

		Loss			
Gain		Concave	Convex	Linear	Total
	Concave	13	5	4	22
	Convex	16	2	2	20
	Linear	0	2	3	5
	Total	29	9	9	47

Table 12. Experiment 2: Classification of convexity of utility functions.

IV. Probability Weighting

For potential gains, the median decision weight of probability 0.5 was 0.38, which did not significantly differ from 0.5 (U = 392, p = .07). The median decision weight was 0.37 for potential losses, indicating significant under-weighting (U = 241, p < .001).

The Matrix Method

The λ values were not significantly different between the earning (median λ = 1.39) and windfall (median λ = 1.18) conditions (U = 185, p = .53), so that the two conditions were collapsed for further analysis of individual differences.

Overall, the median λ was 1.30, which was significantly higher than 1 (U = 790, p < .0001). There were 32 loss-averse and 9 gain-seeking participants; the proportion of loss aversion was significantly higher than the proportion of gain-seeking, $x^2(2) = 11.81$, p < .001 (Figure 7).

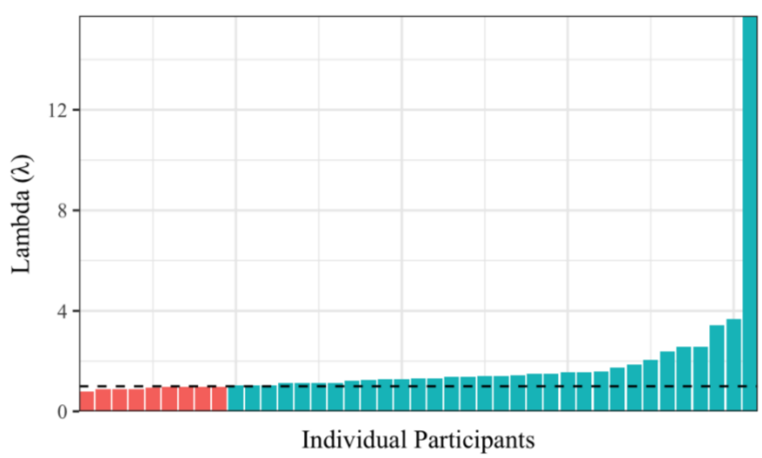

Figure 7. Loss aversion coefficients in community gamblers the matrix method.

Based on the median estimators of the logistic regression, participants had no overall bias to accept or reject the mixed gambles across all levels of gains and losses (β_{Bias} = .12, *p* = .48) (Table 13).

Predictors	$\beta(SE)$	p
Gain	0.35(0.10)	< .0001
Loss	0.53(0.12)	< .0001
Bias	0.12(0.95)	0.48

Table 13. Experiment 2: Median coefficients of the matrix model.

Matrix vs. Staircase

When the λ values were estimated under the same assumptions of linear utility function and no probability weighting, the matrix λ was significantly correlated with the staircase *gain/loss ratio*, *rho*(38) = .36, *p* = .02, supporting the stability of the loss aversion estimates across the matrix and staircase methods. However, λ estimated from the Full model of the staircase method did not correlate with the λ estimated from the matrix model, *rho*(38) = -.07, *p* = .65. Unlike in Experiment 1 with the student sample, in which λ values deviated by the parametric assumption on the utility powers but not the decision weights, the model fit in the community gamblers seemed to be sensitive to both parameters. The partial correlations of λ values between the two models remained weak when controlling the utility power estimators, *rho*(36) = .07, *p* = .69, and the decision weight estimators, *rho*(36) = -.12, *p* = 0.46. Overall, the correlation of λ values weakened when the matrix and staircase model applied different parametric assumptions. This re-emphasizes the sensitivity of model fit and level of loss aversion to the model assumptions in such choice models.

PGSI

In the staircase procedure, the certainty equivalents in the pure gambles revealed the risk attitudes towards potential gains and losses. For pure gains, a smaller certainty equivalent relative to its expected value indicates risk-aversion, while for pure losses, a smaller certainty equivalent relative to its expected value indicates risk-seeking. Among the gain-only gambles, risk aversion was the dominant risk attitude in the non-problem gamblers, $x^2(1) = 13.76$, $p < .001$, and the low-severity gamblers, $x^2(1) = 9.51$, $p < .01$, but not in the moderate-severity gamblers, $x^2(1) = .04$, $p = .84$ (Figure 8). The results indicated that the higher PGSI scores, the higher proportion of risk-seeking choices. In the loss-only gambles, the proportions of risk-seeking and risk-averse choices were similar for the non-problem gamblers, $x^2(1) = .43$, $p = .51$, the low-severity gamblers, $x^2(1) = .35$, $p = .55$, and the moderate-severity gamblers, $x^2(1) = 3.18$, $p = .07$ (Figure 8). That is the PGSI score did not correlate with the proportion of risk-seeking choices.

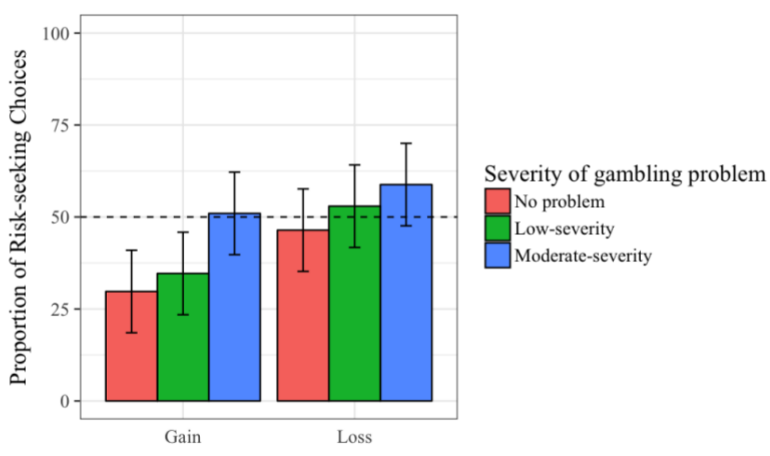

Figure 8. The proportion of risk-seeking across levels of gambling problems.

Table 14 shows the median λ of the groups with varying gambling severity. There was no significant correlation between the PGSI scores and the λ values in the staircase method, *rho*(45) = .20, *p* = .17, or the matrix method , *rho*(39) = -.12, *p* = .44. The PGSI scores did not correlate with the probability weighting estimators δ in the gain domain, *rho*(45) = .13, *p* = .38, or the loss domain, *rho*(45) = -.03, *p* = .83.

		Non-problem	Low-severity	Moderate-severity
Staircase	Median δ^+ (IQR)	0.26 (0.13 - 0.62)	0.38 (0.29 - 0.68)	0.45 (0.28 - 0.64)
	Median δ^- (IQR)	0.37 (0.13 - 0.49)	0.40 (0.22 - 0.52)	0.31 (0.16 - 0.41)
	Median λ (IQR)	0.53 (0.04-1.79)	0.71 (0.04-2.25)	1.03 (0.15-3.06)
Matrix	Median λ (IQR)	1.40 (1.12-1.56)	1.38 (0.98-1.60)	1.24 (1.05-1.39)

Table 14. Experiment 2: Median λ and IQR at each level of severity of problem gambling.

Discussion

Problem gambling is characterized by risky, compulsive betting despite long-term losses, and such behaviour intensifies with gambling severity. Loss aversion, risk attitudes, and probability distortion are three Behavioural Economic variables that determine an individual's behavioural pattern in risky decisions. For instance, low sensitivity towards losses relative to gains would encourage an individual to take more risky choices in mixed gambles; a risk-seeking individual is more attracted to risk itself and prefers a risky gain over a safe gain; over-weighting a winning probability and/or under-weighting a losing probability would encourage more risky choices. Overall, these variables were expected to vary with the severity of gambling problems in my community sample of regular gamblers.

Past literature has tended to focus on single aspects of risky behaviour and usually in the gain or mixed domains, perhaps due to the higher saliency of winnings in problem gambling (Gillespie, Derevensky, and Gupta, 2007). For instance, the only experiment of probability weighting in problem gamblers specifically investigated risky choices in the gain domain

(Ligneul et al., 2013). Loss aversion has been previously examined with risky choices in the mixed domain (Giorgetta et al., 2014; Gelskov et al., 2016; Lorains et al.,2014). The choice models used in some studies were over-simplified; for example, the models neglected probability weighting or the exponential power of the utility function (Giorgetta et al., 2014; Sokol-Hessner et al., 2009; Tom et al., 2007). No studies explored losses-only gambles. The current study uniquely examined loss aversion, risk attitudes, and probability distortion across the gain, loss, and mixed outcome domains in a community sample with varying levels of gambling problems.

Participants were classified into three levels of gambling severity: non-problem, low-severity, and moderate-severity based on their PGSI scores. The severity of gambling problems was not related to the loss aversion coefficients derived from either the matrix or staircase methods.

The current task with 50-50 pure gambles observed the perceived probability at 50% for potential gains and losses. Across all level of gambling severity, participants considerably under-weighted the probability for potential loss outcomes. There was a slight tendency of under-weighting the probability for potential gain outcomes, but the degree of distortion was not significant. Overall, gambling severity was not related to the degree of probability distortion for potential gains or losses.

In the gain domain, the non-problem gamblers and low-severity gamblers used risk-averse strategy dominantly, consistent with the reflection effect in gains. By contrast, the moderate-severity gamblers have reduced risk aversion, to the extent of being risk-neutral. Thus, the percentage of risk-seeking choices increased with the severity of gambling problems. In the loss domain, the reflection effect predicts an overall risk-seeking pattern, although the observed risk attitudes were more ambivalent; that is, they had similar proportions of risk-averse and risk-seeking choices. The increased risk-aversion might be due to real payoffs involved in the gambles, since participants would take loss gambles more seriously (Schoemaker, 1990). Thus, risk attitudes in the gain domain were more predictive of gambling severity than risk attitudes in the loss domain; an individual with more severe gambling problem tended to prefer risky gains over guaranteed gains, whereas the risk attitudes for losses were similar across the level of gambling severity in the healthy samples.

Across the three sets of variables (loss aversion, risk attitudes, and probability distortions), the risk attitude in the gain domain was the only predictor of the severity of gambling problem. The risk preference in the loss-related gambles (i.e., loss-only gambles, mixed gambles) did not predict the severity. This is consistent with the argument that problem gamblers put more priority on winning rather than losses during gambles (Gillespie et al., 2007).

The current study sought to recruit recreational gamblers, and excluded participants scoring in the range for likely Gambling Disorder. The relationships observed between loss aversion, risk attitudes, and probability distortions and the severity of gambling problem may not generalize to the wider continuum of gambling severity including Gambling Disorder; clinically diagnosed problem gamblers could differ qualitatively from healthy gamblers. Hence, any comprehensive conclusions regarding the correlations between the severity of gambling problem and loss aversion, risk attitudes, and probability distortions will require recruitment of individuals with severe Gambling Disorder. That said, there was no evidence to indicate that any of the Behavioural Economic variables are demarcated by clinical diagnosis, and past studies did not generally test correlations with severity or include sub-clinical problem gamblers (i.e., low, moderate- severity). The current study was also limited in terms of experimental controls. Because the loss aversion task was included as a component in a larger project, some extra design features were involved: participants completed a slot machine session, and some questionnaires related to financial attitudes, prior to completing the loss aversion task. These measures could have affected risk attitudes or cognitive exhaustion and change their behaviour on the loss aversion task. Second, the initial endowment from the windfall and money-earning task was for the slot machine play and the loss aversion task together. The non-significant house-money effect in loss aversion might be because participants internalized the endowment as their own following the period of slot machine play.

Chapter 5: General discussion

Loss aversion can be observed by asking an individual to reject or accept mixed gambles. Two measures of loss aversion have been employed in past studies (Giorgetta et al., 2014; Gelskov et al., 2016; Genauck et al., 2017; Lorains et al., 2014; Takeuchi et al., 2016): the matrix and staircase methods. These methods have different task structures and rely on different choice models. A key feature of the current thesis was using both methods to evaluate the consistency in participants' loss aversion. I also reviewed the respective choice models and examined their reliability in estimating loss aversions. The staircase model measured loss aversion under Prospect Theory, by 1) measuring the utility functions of gains and losses independently without assumptions; 2) weighting probabilities for gains and losses independently. By contrast, the matrix method assumed linear utility functions and no probability weighting for gains and losses. As a result, the two methods ranked participants' level of loss aversion differently within both Experiment 1 and Experiment 2.

In Experiment 1 on the staircase method, participants significantly under-weighted probability at 50% for potential gains and losses. This probability distortion led to considerably skewed curvatures of utility functions, which ultimately influenced loss aversion coefficients. Because the matrix model did not allow variations in the utility function and probability weighting of 50%, the assumptions deviated the level of loss aversion away from the results of the staircase method. Similarly, in the Experiment 2 data from the staircase method, participants significantly under-weighted the probability for potential losses, leading to a non-linear curvature of the utility function; the probability weighting was not significant for potential gain, leading to a linear curvature. The parameters of probability weight and utility power in the loss domain deviated from the matrix method's assumptions, and thus the two methods again derived different degrees of loss aversion. When the two models used the consistent assumptions of linear utility functions and no probability weighting, their loss aversion coefficients became significantly correlated in both the student and community gambler samples. The improved correlation indicated that level of loss aversion was stable across the matrix and staircase methods, but the model assumptions compromise the inter-relationships of the two measurements. Some studies have argued that probability weighting at 50% is negligible (Gonzalez, 1999; Prelec, 1998), but the current findings suggested that the degree of probability distortion is significant even in the central range. Hence, it is necessary to have a non-parametric model for the probability weighting in the utility measurement, otherwise, the loss aversion coefficients may be biased.

In chapter 1, I outlined four hypotheses which proposed to conclude the influence of outcome feedback on loss aversion and explain risk-seeking behaviour in sub-clinical problem gamblers. First, participants in the Feedback condition had a similar level of loss aversion, although a tendency of larger loss aversion coefficients in the No-feedback condition presented across the matrix and staircase methods. The null difference might be due to the small magnitudes of gambles, which lowered sensitivity towards losses significantly (Harinck et al., 2007; Mukherjee et al., 2017), and overrode the potential feedback effect.

Second, the correlation between loss aversion and the severity of gambling problem was weak in the sub-clinical problem gamblers, and the level of loss aversion was similar across non-problem gamblers, low-severity gamblers, and moderate-severity gamblers. But because the participant samples did not include gamblers with a highly severe gambling problem (i.e., pathological gamblers), the results do not rule out the possibility that loss aversion coefficients could be abnormal at higher levels of gambling severity.

Third, the current task only measured the probability weighting at 50%. Based on the elevation hypothesis (Ligneul et al., 2013), problem gamblers were expected to over-weight the gain probability at 50% more than the healthy control group, displaying a probability weighting function that is shifted upwards across the whole probability range (Ligneul et al., 2013; Takeuchi et al., 2018). In contrast, the severity of gambling problem did not correlate with the scale of probability distortions for potential gains in the current study. A recent study (Takeuchi et al., 2018) found that the probability weighting function of problem gamblers did not shift significantly in the loss domain relative to the healthy control group. Consistent with Takeuchi et al., (2018), the correlation between the severity of gambling problem and the scale of probability distortions for potential losses was weak in this current study.

Fourth, gamblers with more severe gambling problem did display more risk-seeking choices in the gain domain, but not in the loss domain. All participants were ambivalent between the risk-seeking and risk-averse strategies for losses. Overall, the risk attitudes in the gain domain was the only Behavioural Economic variable that predicted the severity of gambling problems. This may be because more excessive gamblers attached higher salience to winning, manifested in a positive expectation of enjoyment, excitement, and monetary profit (Gillespie et al., 2007). Risk-seeking on the loss gambles was not correlated with the severity of gambling problems. Similar with the non-problem gamblers, probable pathological gamblers were too highly aware of their preoccupation with gambling and perceived potential problem in the over-involvement (Gillespie et al., 2007).

Individuals with gambling problems are characterized by the higher tendency of compulsive betting pattern despite losses, hypothetically reflecting a preference for risk. The current thesis showed that the risk-seeking choices increased with the severity of gambling problem in the gain domain. This risk-seeking attitude might be explained by the lower risk perception with elevated probability weighting function (Ligneul et al., 2013; Takeuchi et al., 2018). Alternatively, risk-taking behaviour could be explained as a failure of adapting one's reference points over successive changes in wealth. Gains and losses are defined relative to a reference point (Kahneman et al., 1979; Kahneman et al., 1992), if an individual failed to re-reference to the current wealth position, new outcomes will be evaluated differently, in relation to a 'wrong' reference point that does not coincide with the current financial status (Thaler and Johnson, 1990). People tend to adapt to positive wealth changes more rapidly than to negative wealth changes; in particular, a healthy individual only became significantly more risk-seeking after experiencing a larger loss relative to others (Chao, Ho, and Qin, 2017). This finding suggests a failure of re-referencing is more likely to occur in the loss domain, whereby relative losses can encourage risk-taking. Future studies may usefully investigate these differences in reference point adaptation in problem gamblers and healthy controls. I speculate that problem gamblers are more likely to have discrepancies between their current wealth status and reference point, which lead to more risk-taking behaviour after losses.

References

Abdellaoui, M., Bleichrodt, H., & l'Haridon, O. (2008). A tractable method to measure utility and loss aversion under prospect theory. *Journal of Risk and uncertainty*, *36*(3), 245. https://link.springer.com/article/10.1007/s11166-008-9039-8.

American Psychiatric Association (2013). *Diagnostic and statistical manual of mental disorders* (5th ed.). Washington, DC: Author. https://doi.org/10.1176/appi.books.9780890425596.

Anselme, P., Robinson, M. J., & Berridge, K. C. (2013). Reward uncertainty enhances incentive salience attribution as sign-tracking. *Behavioural brain research*, *238*, 53-61. doi: 10.1016/j.bbr.2012.10.006.

Bernoulli, D. (1954). Exposition of a new theory on the measurement of risk. *Econometrica*, 22, 23-36. (Original work published 1738). doi: 10.2307/1909829.

Bechara, A., Damasio, A. R., Damasio, H., & Anderson, S. W. (1994). Insensitivity to future consequences following damage to human prefrontal cortex. *Cognition*, *50*(1-3), 7-15. https://www.ncbi.nlm.nih.gov/pubmed/8039375.

Benartzi, S., & Thaler, R. H. (1995). Myopic loss aversion and the equity premium puzzle. *The quarterly journal of Economics*, *110*(1), 73-92. doi: 10.3386/w4369.

Brand, M., Kalbe, E., Labudda, K., Fujiwara, E., Kessler, J., & Markowitsch, H. J. (2005). Decision-making impairments in patients with pathological gambling. *Psychiatry research*, *133*(1), 91-99. doi: 10.1016/j.psychres.2004.10.003.

Brooks, P., & Zank, H. (2005). Loss averse behavior. *Journal of Risk and Uncertainty*, *31*(3), 301-325. https://link.springer.com/article/10.1007/s11166-005-5105-7.

Baucells, M., & Villasís, A. (2010). Stability of risk preferences and the reflection effect of prospect theory. *Theory and Decision*, *68*(1-2), 193-211. https://link.springer.com/article/10.1007/s11238-009-9153-3

Brevers, D., Cleeremans, A., Goudriaan, A. E., Bechara, A., Kornreich, C., Verbanck, P., & Noël, X. (2012). Decision making under ambiguity but not under risk is related to problem gambling severity. *Psychiatry research*, *200*(2-3), 568-574. doi: 10.1016/j.psychres.2012.03.053.

Brevers, D., Bechara, A., Cleeremans, A., & Noël, X. (2013). Iowa Gambling Task (IGT): twenty years after–gambling disorder and IGT. *Frontiers in psychology*, *4*, 665. doi: 10.3389/fpsyg.2013.00665.

Barry, J. (2014). *British Columbia problem gambling prevalence study*. Ministry of Public Safety and Solicitor General, Canada. https://www2.gov.bc.ca/assets/gov/sports-recreation-arts-and-culture/gambling/gambling-in-bc/reports/rpt-rg-prevalence-study-2014.pdf.

Conlisk, J. (1993). The utility of gambling. *Journal of Risk and uncertainty*, *6*(3), 255-275. https://www.jstor.org/stable/41760686?seq=1#page_scan_tab_contents.

Cox, B. J., Kwong, J., Michaud, V., & Enns, M. W. (2000). Problem and probable pathological gambling: considerations from a community survey. *The Canadian Journal of Psychiatry*, *45*(6), 548-553. doi: 10.1177/070674370004500606.

Camerer, C. (2005). Three cheers—psychological, theoretical, empirical—for loss aversion. *Journal of Marketing Research*, *42*(2), 129-133. doi: 10.1509/jmkr.42.2.129.62286.

Campbell-Meiklejohn, D. K., Woolrich, M. W., Passingham, R. E., & Rogers, R. D. (2008). Knowing when to stop: the brain mechanisms of chasing losses. *Biological psychiatry, 63*(3), 293-300. doi: 10.1016/j.biopsych.2007.05.014.

Calado, F., & Griffiths, M. D. (2016). Problem gambling worldwide: an update and systematic review of empirical research (2000–2015). *Journal of behavioral addictions*, *5*(4), 592-613. doi: 10.1556/2006.5.2016.073.

Chao, H., Ho, C. Y., & Qin, X. (2017). Risk taking after absolute and relative wealth changes: The role of reference point adaptation. *Journal of Risk and Uncertainty*, *54*(2), 157-186. doi: 10.1007/s11166-017-9257-z.

Damasio, A. R. (1996). The somatic marker hypothesis and the possible functions of the prefrontal cortex. *Phil. Trans. R. Soc. Lond. B*, *351*(1346), 1413-1420. doi: 10.1098/rstb.1996.0125.

De Martino, B., Camerer, C. F., & Adolphs, R. (2010). Amygdala damage eliminates monetary loss aversion. *Proceedings of the National Academy of Sciences*, *107*(8), 3788-3792. doi: 10.1073/pnas.0910230107.

Elster, J., & Roemer, J. E. (Eds.). (1993). *Interpersonal comparisons of well-being*. Cambridge, UK: Cambridge University Press.

Ert, E., & Erev, I. (2013). On the descriptive value of loss aversion in decisions under risk: Six clarifications. *Judgment and Decision Making*, 8, 214 –235. doi: 10.2139/ssrn.1012022.

Ferris, J. A., & Wynne, H. J. (2001). *The Canadian problem gambling index*. Ottawa, ON: Canadian Centre on Substance Abuse.

Fortune, E. E., & Goodie, A. S. (2012). Cognitive distortions as a component and treatment focus of pathological gambling: a review. *Psychology of Addictive Behaviors*, *26*(2), 298. doi: 10.1037/a0026422.

Ferentzy, P., & Turner, N. E. (2013). *The history of problem gambling*. New York, NY: Springer.

Gonzalez, R., & Wu, G. (1999). On the shape of the probability weighting function. *Cognitive psychology*, *38*(1), 129-166. doi: 10.1006/cogp.1998.0710.

Gläscher, J., & Adolphs, R. (2003). Processing of the arousal of subliminal and supraliminal emotional stimuli by the human amygdala. *Journal of Neuroscience, 23*(32), 10274-10282. https://doi.org/10.1523/JNEUROSCI.23-32-10274.2003.

Goudriaan, A. E., Oosterlaan, J., de Beurs, E., & van den Brink, W. (2006). Psychophysiological determinants and concomitants of deficient decision making in pathological gamblers. *Drug and alcohol dependence*, *84*(3), 231-239. doi: 10.1016/j.drugalcdep.2006.02.007.

Gillespie, M. A., Derevensky, J., & Gupta, R. (2007). The utility of outcome expectancies in the prediction of adolescent gambling behaviour. *Journal of Gambling Issues*, (19), 69-85. http://dx.doi.org/10.4309/jgi.2007.19.4.

Grant, J. E., Odlaug, B. L., Chamberlain, S. R., & Schreiber, L. R. (2012). Neurocognitive dysfunction in strategic and non-strategic gamblers. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, *38*(2), 336-340. https://doi.org/10.1016/j.pnpbp.2012.05.006.

Giorgetta, C., Grecucci, A., Rattin, A., Guerreschi, C., Sanfey, A. G., & Bonini, N. (2014). To play or not to play: a personal dilemma in pathological gambling. *Psychiatry research*, *219*(3), 562-569. doi: 10.1016/j.psychres.2014.06.042.

Gelskov, S. V., Madsen, K. H., Ramsøy, T. Z., & Siebner, H. R. (2016). Aberrant neural signatures of decision-making: Pathological gamblers display cortico-striatal hypersensitivity to extreme gambles. *NeuroImage*, *128*, 342-352. doi: 10.1016/j.neuroimage.2016.01.002.

Genauck, A., Quester, S., Wüstenberg, T., Mörsen, C., Heinz, A., & Romanczuk-Seiferth, N. (2017). Reduced loss aversion in pathological gambling and alcohol dependence is associated with differential alterations in amygdala and prefrontal functioning. *Scientific reports*, *7*(1), 16306. doi: 10.1038/s41598-017-16433-y.

Harinck, F., Van Dijk, E., Van Beest, I., & Mersmann, P. (2007). When gains loom larger than losses: Reversed loss aversion for small amounts of money. *Psychological science*, *18*(12), 1099-1105. doi: 10.1111/j.1467-9280.2007.02031.x.

Hodgins, D. C., Stea, J. N., & Grant, J. E. (2011). Gambling disorders. *The Lancet*, *378*(9806), 1874-1884. https://doi.org/10.1016/S0140-6736(10)62185-X.

Ikemoto, S., Yang, C., & Tan, A. (2015). Basal ganglia circuit loops, dopamine and motivation: a review and enquiry. *Behavioural brain research*, *290*, 17-31. doi: 10.1016/j.bbr.2015.04.018.

Knight, F. H. (1921). *Risk, uncertainty and profit*. New York, NY: Hart, Schaffner and Marx.

Kahneman, D., & Tversky. A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica,* 47, 263-291. doi: 10.2307/1914185.

Kühberger, A. (1998). The influence of framing on risky decisions: A meta-analysis. *Organizational behavior and human decision processes*, *75*(1), 23-55. https://doi.org/10.1006/obhd.1998.2781.

Ladouceur, R. (1996). The prevalence of pathological gambling in Canada. *Journal of gambling studies*, *12*(2), 129-142. doi: 10.1007/BF01539170.

Ladouceur, R., & Walker, M. (1996). A cognitive perspective on gambling. *Trends in cognitive and behavioural therapies*, 89-120.

Langer, T., & Weber, M. (2008). Does commitment or feedback influence myopic loss aversion?: An experimental analysis. *Journal of Economic Behavior & Organization*, *67*(3-4), 810-819. doi:10.1016/j.jebo.2006.05.019.

Lawrence, A. J., Luty, J., Bogdan, N. A., Sahakian, B. J., & Clark, L. (2009). Impulsivity and response inhibition in alcohol dependence and problem gambling. *Psychopharmacology*, *207*(1), 163-172. doi: 10.1007/s00213-009-1645-x.

Linnet, J., Peterson, E., Doudet, D. J., Gjedde, A., & Møller, A. (2010). Dopamine release in ventral striatum of pathological gamblers losing money. *Acta Psychiatrica Scandinavica*, *122*(4), 326-333. doi: 10.1111/j.1600-0447.2010.01591.x.

Ligneul, R., Sescousse, G., Barbalat, G., Domenech, P., & Dreher, J. C. (2013). Shifted risk preferences in pathological gambling. *Psychological medicine*, *43*(5), 1059-1068. doi: 10.1017/S0033291712001900.

Lorains, F. K., Dowling, N. A., Enticott, P. G., Bradshaw, J. L., Trueblood, J. S., & Stout, J. C. (2014). Strategic and non-strategic problem gamblers differ on decision-making under risk and ambiguity. *Addiction, 109*(7), 1128-1137. doi: 10.1111/add.12494.

Mullainathan, S., & Thaler, R. H. (2000). *Behavioral economics* (Working Paper No. W7948). National Bureau of Economic Research. doi: 10.3386/w7948.

McGaugh, J. L. (2004). The amygdala modulates the consolidation of memories of emotionally arousing experiences. *Annual Review of Neuroscience.*, *27*, 1-28. doi: 10.1146/annurev.neuro.27.070203.144157.

Milosevic, A., & Ledgerwood, D. M. (2010). The subtyping of pathological gambling: A comprehensive review. *Clinical Psychology Review*, *30*(8), 988-998. doi: 10.1016/j.cpr.2010.06.013.

Mukherjee, S., Sahay, A., Pammi, V. C., & Srinivasan, N. (2017). Is loss-aversion magnitude-dependent? Measuring prospective affective judgments regarding gains and losses. *Judgment and Decision Making*, *12*(1), 81. http://journal.sjdm.org/16/16611/jdm16611.pdf.

Navon, D. (1977). Forest before trees: The precedence of global features in visual perception. *Cognitive psychology*, *9*(3), 353-383. https://doi.org/10.1016/0010-0285(77)90012-3.

Prelec, D. (1998). The probability weighting function. *Econometrica*, 66, 497–527. doi: 10.2307/2998573.

Petry, N. M. (2003). A comparison of treatment-seeking pathological gamblers based on preferred gambling activity. *Addiction*, *98*(5), 645-655. doi: 10.1046/j.1360-0443.2003.00336.x.

Preuschoff, K., Bossaerts, P., & Quartz, S. R. (2006). Neural differentiation of expected reward and risk in human subcortical structures. *Neuron*, *51*(3), 381-390. doi: 10.1016/j.neuron.2006.06.024.

Royden, H. L., Suppes, P., & Walsh, K. (1959). A model for the experimental measurement of the utility of gambling. *Behavioral Science*, *4*(1), 11-18. https://doi.org/10.1002/bs.3830040103.

Raylu, N., & Oei, T. P. (2002). Pathological gambling: A comprehensive review. *Clinical psychology review*, *22*(7), 1009-1061. doi: 10.1016/j.neubiorev.2004.03.001.

Roca, M., Torralva, T., López, P., Cetkovich, M., Clark, L., & Manes, F. (2008). Executive functions in pathologic gamblers selected in an ecologic setting. *Cognitive and Behavioral Neurology*, *21*(1), 1-4. doi: 10.1097/WNN.0b013e3181684358.

Schoemaker, P. J. (1990). Are risk-attitudes related across domains and response modes?. *Management science*, *36*(12), 1451-1463. https://doi.org/10.1287/mnsc.36.12.1451.

Schwartz, D. (2006). *Roll the bones.* New York, NY: Gotham Books.

Stott, H. P. (2006). Cumulative prospect theory's functional menagerie. *Journal of Risk and uncertainty*, *32*(2), 101-130. doi: 10.1007/s11166-006-8289-6.

Sokol-Hessner, P., Hsu, M., Curley, N. G., Delgado, M. R., Camerer, C. F., & Phelps, E. A. (2009). Thinking like a trader selectively reduces individuals' loss aversion. *Proceedings of the National Academy of Sciences*, *106*(13), 5035-5040. https://doi.org/10.1073/pnas.0806761106.

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

Sokol-Hessner, P., Camerer, C. F., & Phelps, E. A. (2012). Emotion regulation reduces loss aversion and decreases amygdala responses to losses. *Social cognitive and affective neuroscience*, *8*(3), 341-350. doi: 10.1093/scan/nss002.

Shen, L., Fishbach, A., & Hsee, C. K. (2014). The motivating-uncertainty effect: Uncertainty increases resource investment in the process of reward pursuit. *Journal of Consumer Research*, *41*(5), 1301-1315. doi: 10.1086/679418.

Spurrier, M., & Blaszczynski, A. (2014). Risk perception in gambling: A systematic review. *Journal of Gambling Studies*, *30*(2), 253-276. doi: 10.1007/s10899-013-9371-z.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *science*, *185*(4157), 1124-1131. doi: 10.1126/science.185.4157.1124.

Thaler, R. H., & Johnson, E. J. (1990). Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice. *Management science*, *36*(6), 643-660. https://doi.org/10.1287/mnsc.36.6.643.

Tom, S. M., Fox, C. R., Trepel, C., & Poldrack, R. A. (2007). The neural basis of loss aversion in decision-making under risk. *Science, 315*(5811), 515-518. doi: 10.1126/science.1134239.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and uncertainty*, *5*(4), 297-323. https://www.jstor.org/stable/41755005.

Takeuchi, H., Kawada, R., Tsurumi, K., Yokoyama, N., Takemura, A., Murao, T., Murai, T., & Takahashi, H. (2016). Heterogeneity of loss aversion in pathological gambling. *Journal of gambling studies*, *32*(4), 1143-1154. doi: 10.1007/s10899-015-9587-1.

Takeuchi, H., Tsurumi, K., Murao, T., Mizuta, H., Murai, T., & Takahashi, H. (2018). Amygdala volume is associated with risky probability cognition in gambling disorder. *Addiction biology*. doi: 10.1111/adb.12640.

Weber, R. A. (2003). 'Learning' with no feedback in a competitive guessing game. *Games and Economic Behavior*, 44, 134–144. https://doi.org/10.1016/S0899-8256(03)00002-2.

Wilson, T. D., Centerbar, D. B., Kermer, D. A., & Gilbert, D. T. (2005). The pleasures of uncertainty: prolonging positive moods in ways people do not anticipate. *Journal of personality and social psychology*, *88*(1), 5. doi: 10.1037/0022-3514.88.1.5.

Wakker, P. P. (2008). Explaining the characteristics of the power (CRRA) utility family. *Health economics*, *17*(12), 1329-1344. doi: 10.1002/hec.1331.

Zeelenberg, M., & Pieters, R. (2004). Consequences of regret aversion in real life: The case of the Dutch postcode lottery. *Organizational Behavior and Human Decision Processes*, *93*(2), 155-168. https://doi.org/10.1016/j.obhdp.2003.10.001.