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album nr. 3745

Magnitude and Context Effects in Preference Reversals

[Efekty wielkości i kontekstu w odwracaniu preferencji wyboru]

A doctoral dissertation prepared under the supervision of

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w Warszawie

Warszawa, 2022

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Abbreviations

ANOVA Analyses of Variance

BDM Becker-DeGroot-Marschak

C? Did You Choose the Bet?

ce Certainty Equivalent

CI Confidence Interval

CNY Chinese Currency Yuan

C or R? Did You Choose or Reject the Bet?

COVID-19 Corona Virus Disease 2019

eu Expected Utility

EUT Expected Utility Theory

EV Expected Value

EVD Expected Value Difference

EVL Expected Value Level

gdu Gains Decomposition Utility

GDUT Gains Decomposition Utility Theory

HSD Honestly Significant Difference

I (Monetary) Incentives

ISI Interstimulus Interval

LOESS Locally Estimated Scatterplot Smoothing

M Mean

MAD Median Absolute Deviation

NI No (Monetary) Incentives

NP Not Played-out

P Played-out

PLN Polish Currency Złoty

PR Preference Reversal

PT Prospect Theory

ptu Prospect Theory Utility

Q1 First Quartile

Q3 Third Quartile

R? Did You Reject the Bet?

rdu Rank-Dependent Utility

RDUT Rank-Dependent Utility Theory

RR Risk Ratio

rp Risk Premium

SD Standard Deviation

SE Standard Error

swau Subjectively Weighted Average Utility

SWAUT Subjectively Weighted Average Utility Theory

SWPS Szkoła Wyższa Psychologii Społecznej

UKSW Uniwersytet Kardynała Stefana Wyszyńskiego w Warszawie

UJ Uniwersytet Jagielloński

Abstract

Preference reversal (PR) reveals that preferences over risky bets can be reversed between choices and willingness-to-accept or -pay. The present research extended limited previous studies on magnitude effects of gains on PR by examining this effect with both gains and losses. Experiment 1: Magnitude effects in PR progressively manipulated the payoff variations in bet pairs to measure the effect of ratio scales on risk preferences and PR. Undergraduates (N = 137) were asked to choose a bet they prefer from a list of bet pairs, and then to evaluate the bets indicating how much they were willing to pay for a chance to participate in each of the bets. We observed a robust dichotomous pattern of choice behavior: The majority of choices are consistent with risk aversion or risk-seeking behavior when loss ratios between bet pairs are no more than -2.5 or no less than -8.0, respectively. Moreover, different patterns of PR can be elicited with these loss stakes.

Experiment 2: Binary choices in PR examined the predictions of three decision-making heuristics, namely a novel simplified approach called the loss-averse rule, the majority rule, and the equate-to-differentiate rule, as well as cumulative prospect theory that individuals may use in binary choice. Participants (N = 113) were asked to choose a bet from a list of bet pairs. We found that when the loss ratio is more than -3.0 at the level of the data, proportions of choices were in the direction predicted by cumulative prospect theory and the loss-averse rule of decision rather than by the other two rules, at both the conditional and aggregate levels. These results suggest that when loss risk reaches a level of threshold, risk behavior for binary choices on lotteries is ubiquitously influenced by loss aversion rather than by the process of value maximization.

To date, neither has literature in gambling situations paid attention to whether the

expected value difference between bet pairs affects the likelihood of PR, almost nor has empirical research shed light on whether episodic memory is involved in PR. In a laboratory-based study, Experiment 3: Episodic memory in PR varied bet pairs in expected value in a market-like scenario. Undergraduates (N = 64) first completed classic dual-procedure PR tasks and then performed a memory test for previous choices. Consistent with past work, participants exhibited non-negligible and systematic rates of PR between choices and valuations. The results suggest a tendency that the larger the expected value difference *between* bet pairs, the larger the predicted PR rate, and provide the first evidence that correct retrievals of initial choices can ameliorate PR.

In a subsequent Experiment 4: Episodic memory in attraction effect PR, participants (N = 86) were incentivized to complete choice and price PR tasks and a memory test on purely risky bets in a pictorial form. We found equivocal evidence of the effect of expected value difference *within* bet pairs on attraction effect PR, no effect of expected value difference or level on correct recollections, and again substantial evidence that correct retrievals of initial choices can ameliorate PR.

Despite the voluminous evidence in support of the paradoxical finding that PR rates can disappear, the question of whether and when small and large loss or gain ratios influence choice between safe and risky bets and impede PR remains open. In three meta-analyses of 12 experiments or treatments reported by 7 prior and current studies (N = 884), we showed that neither low nor high loss or gain ratios are more powerful—a finding counter to the data reported in Experiment 1: Magnitude effects in PR and Experiment 3: Episodic memory in PR. We also identified no indications that the PR design (gain-zero or gain-loss) or the evaluation mode (separate or join) influences safe bet choice and PR sizes. As the first meta-analytic research on this phenomenon, we reasoned possible factors that may cause

those conflicting results.

Overall, these results (1) reaffirm the existence of the traditional and contextual PR phenomenon, (2) indicate the fragile, context-dependent nature of PR phenomenon, (3) provide evidence about how memory retrieval operates as individuals perform binary choice and pricing tasks, and (4) may have implications for eliciting risk preferences by the specific construction of payoffs and EVs in gambling and decision making. A number of limitations in terms of materials and methods are addressed along with future research that may test other evidence of magnitude and context effects in PR.

Keywords: preference reversal, risk preference, loss-averse rule, episodic memory, expected value difference, attraction effect

Streszczenie

Zjawisko odwracania preferencji (preference reversal, PR) ujawnia, że preferencje dotyczące ryzykownych zakładów mogą ulec odwróceniu między sytuacją wyboru a deklaracją gotowości do przyjęcia lub zapłacenia. Przedstawione w dysertacji badania poszerzają – dotychczas ograniczone – studia nad efektem wielkości wypłat na PR poprzez badania tego efektu zarówno z zyskami jak i stratami. Eksperyment 1: Efekt wielkości w PR, wprowadził stopniową manipulację zmianami wypłat w parach zakładów w celu pomiaru efektu proporcji skal na preferencję ryzyka i PR. Studenci ($N = 137$) zostali poproszeni o wybranie zakładów, które preferują z listy par zakładów, a następnie o ponowną ocenę tych zakładów poprzez określenie kwoty jaką byliby gotowi zapłacić za szansę uczestnictwa w każdym z tych zakładów. Zaobserwowano wyraźny dychotomiczny wzór wyborów; gdy proporcje strat między parami zakładów były nie większe niż –2,5, większość wyborów była zgodna z awersją ryzyka, natomiast gdy proporcja strat była nie mniejsza niż –8,0, w wyborach przejawiało się poszukiwanie ryzyka. Ponadto każda z tych stawek strat prowokowała odmienne wzorce PR.

Eksperyment 2: Binarne wybory w PR zestawił przewidywania trzech różnych heurystyk podejmowania decyzji. Wśród analizowanych reguł używanych w binarnych wyborach były: nowe uproszone podejście zwane regułą unikania straty, reguła większości oraz reguła wyrównania-aby-zróżnicować, zbadano także przewidywania kumulatywnej teorii perspektywy. Uczestników eksperymentu ($N = 113$) proszono o wybranie zakładów z listy par zakładów. Zauważono, że gdy na poziomie danych proporcja straty była większa niż –3,0, wzorzec wyborów był w większym stopniu zgodny z kierunkiem przewidywanym przez kumulatywną teorię perspektywy oraz regułę unikania straty niż z przewidywaniami dwu pozostałych reguł, zarówno

na poziomie warunkowym jak i zbiorczym. Wyniki te sugerują, że gdy ryzyko straty osiąga pewien poziom progowy, ryzykowne zachowania w binarnych wyborach loterii jest raczej pod całkowitym wpływem awersji ryzyka niż dążenia do maksymalizacji wartości.

Jak dotąd literatura na temat decyzji w zakładach hazardowych nie zwracała uwagi na to, czy różnice w wartościach oczekiwanych między parami zakładów wpływają na prawdopodobieństwo wystąpienia PR. Podobnie niewiele jest badań, które rzuciłyby światło na rolę pamięci epizodycznej w PR. Przeprowadzony w warunkach laboratoryjnych Eksperyment 3: Pamięć epizodyczna w PR polegał na systematycznych zmianach wartości oczekiwanych par zakładów w scenariuszu imitującym sytuację rynkową. Badani studenci ($N = 64$) najpierw uczestniczyli w klasycznej podwójnej procedurze zadania PR, a następnie wykonali test pamięci odwołujący się do dokonanych uprzednio wyborów. Zgodnie z wynikami wcześniejszych prac uczestnicy uzyskali niezaniedbywalne i systematyczne wskaźniki odwróceń preferencji między wyborami a wycenami. Rezultaty dostarczyły pierwszych dowodów na to, że im większe są różnice w wartościach oczekiwanych między parami zakładów, tym większy jest poziom prognozowanego (tzn. zgodnego z klasycznym wzorcem) PR. Co więcej wykazano, że poprawne przypomnienia początkowych wyborów mogą złagodzić PR.

W kolejnym Eksperymencie 4: Pamięć epizodyczna w efekcie przyciągania w PR (*attraction effect PR*) uczestnicy ($N = 86$) byli motywowani wynagrodzeniem do wykonania zadań wyboru i wyceny oraz testu pamięci dotyczącego wyłącznie ryzykownych zakładów przedstawionych w formie obrazkowej. Zaobserwowany wpływ różnic w wartościach oczekiwanych wewnątrz par zakładów na efekt przyciągania w PR okazał się niejednoznaczny, nie wystąpił efekt różnicy ani poziomu wartości oczekiwanej na poprawne przypomnienia. Natomiast potwierdzona została obserwacja o tym, że poprawnym przypomnieniom początkowego wyboru towarzyszy osłabienie PR.

Pomimo obszernych dowodów na poparcie paradoksalnego odkrycia, że PR może zanikać, pytanie, czy i kiedy małe i duże współczynniki straty lub zysku wpływają na wybór między bezpiecznymi i ryzykownymi zakładami i utrudniają PR, pozostaje otwarte. W trzech metaanalizach 12 eksperymentów lub procedur opisanych przez 7 wcześniejszych i obecnych badań ($N = 884$), wykazaliśmy, że ani niskie, ani wysokie współczynniki straty lub zysku nie są silniejsze - odkrycie to jest niezgodne z danymi przedstawionymi w Eksperyment 1: Efekt wielkości w PR i Eksperyment 3: Pamięć epizodyczna w PR. Nie zidentyfikowaliśmy również żadnych przesłanek wskazujących na to, że konstrukcja PR (zysk-zero lub zysk-strata) lub tryb oceny (oddzielny lub łączony) wpływają na wybór bezpiecznego zakładu i wielkość PR. Jako że było to pierwsze metaanalityczne badanie tego zjawiska, rozważyliśmy możliwe czynniki, które mogą powodować te sprzeczne wyniki.

Generalnie uzyskane wyniki (1) potwierdzają występowanie standardowego i kontekstowego zjawiska PR, (2) wskazują na kruchą i zależną od kontekstu naturę zjawiska PR, (3) dostarczają obserwacji empirycznych dotyczących tego, jaką rolę odgrywa wydobywanie z pamięci wcześniejszych wyborów, gdy osoby wykonują zadania binarnych wyborów i wycen oraz (4) mogą mieć implikacje dla wywoływania preferencji ryzyka poprzez specyficzną konstrukcję wypłat i wartości oczekiwanych w zakładach losowych i podejmowaniu decyzji. Odniesiono się do szeregu ograniczeń w zakresie materiałów i metod oraz przedstawiono perspektywy przyszłych badań, które mogą sprawdzić inne dowody na efekty wielkości i kontekstu w PR.

Słowa kluczowe: odwracanie preferencji, preferencja ryzyka, reguła awersji straty, pamięć epizodyczna, różnica wartości oczekiwanej, efekt przyciągania

Declarations

Authorship

The author declares that this thesis and the work presented in it are my own. The author confirms that:

- No portion of the work referred to in this thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.
- This work was done wholly while in candidature for a research degree at this University.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of uch quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Funding

A part of Experiment 2: Binary choices in PR and the whole Experiment 4: Episodic memory in attraction effect PR were supported by Statutory Fund DEC-IP-6/20 from Cardinal Stefan Wyszyński University in Warsaw, Poland.

Conflicts of interest/Competing interests

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Ethics approval

As the research presented no more than minimal risk of harm to the participants and involved no procedures for which written consent is normally required outside the study context, a verbal informed consent was provided to the participants in Experiment 1: Magnitude effects in PR, a partial Experiment 2: Binary choices in PR, and Experiment 3: Episodic memory in PR in lieu of signed informed consent. The experimenters read out loud the verbal informed consent at the outset. For the rest Experiment 2: Binary choices in PR and Experiment 4: Episodic memory in attraction effect PR, the participants received the written consent.

Consent to participate

All the participants provided consent.

Availability of data and material

Data are included as electronic supplementary material at the Open Science Framework website, at https://osf.io/efdv4. We also declare that the data include all measures and conditions. Unless otherwise noted, no data are excluded from the analysis.

Code availability

Data are included as electronic supplementary material at the Open Science Framework website, at https://osf.io/3ypt6.

Alternative format statement

This work is submitted in the alternative format. The conjoint content (Sub-)Sections and Appendixes are written as standalone journal article or conference abstract. These were either published (Sections 1, 1.4, 2.1, 2.2, 5, and 6, and Appendixes A, B, C, D.2, D.3, E.1, E.2, F) or are under review (Sections 1.1, 1.2, 2.3, 2.4, 2.5, 7, and 8 and Appendixes D.4, D.5, E.3, E.4, G, and I). In all Sections and Appendixes, I am the first or solo author, along with my supervisor, prof. UKSW dr hab. Marek Nieznański. Together, these sections form a coherent thread of research which is outlined in more detail in Section 1 Introduction.

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Acknowledgments

I owe an extraordinarily special debt of gratitude to my supervisor, prof. UKSW dr hab. Marek Nieznański, who gave continued support and advice on my study and the drafts of this work. Without his help this work has never been possible to complete. I also thank the reviewers of an earlier version of this work, prof. SWPS dr hab. Wojciech Białaszek and prof. UJ dr hab. Szymon Wichary, for profoundly helpful comments.

Other various academics have contributed to my study at UKSW with advice, guidance, and assistance. For their help I would like to thank the following people: ks. prof. dr hab. Bartosz Adamczewski, prof. dr hab. Jan Cieciuch, ks. prof. dr hab. Andrzej Kobyliński, ks. prof. dr hab. Janusz Kręcidło, and ks. prof. dr hab. Tomasz Stępień. With special thanks to ks. prof. dr hab. Bogumił Gacka for the hospitality of his family hosting me during the Christmas holiday in 2015 in Koło, the heart of Poland.

I also gratefully acknowledge financial support from the Statutory Fund of UKSW, grant no. DEC-IP-6/20. Particularly, prof. dr hab. Marek Nieznański translated the abstract into Polish, dr. Jarosław Jastrzebski helped run the paper-and-pencil part of Experiment 2: Binary choices in PR, Mgr. Michał Obidziński helped run Experiment 3: Episodic memory in PR in E-Prime, and Mgr. Justyna Jastrzębska translated the participation instruction in Experiment 4: Episodic memory in attraction effect PR into Polish, all at the Faculty of Christian Philosophy, UKSW.

Finally, I thank my friends Raimonds Kīne (Latvia), Tajana Krnčanová (Slovakia), Pavla Strýčková (Czech Republic), and Adam Terwinski (Poland). I am thankful to my parents, and my wife Xiao-Li for their continuing love and support.

1. Introduction

The conception of economic rationality presumes that human decision making should abide by normative theories. However, there exists a gap between normative economics of what decisions *should* be made and descriptive psychological theories of what decisions *are* made. Since Simon (1955) rejected the rational man of economics and defined *bounded rationality*, a significant amount of experimental and field evidence has suggested that people usually do not make perfect decisions, due to inner or outer restrictions such as cognitive limitations, logical errors, false memory, pressured time allocation, or varying contents. The concept of bounded rationality inspired seminal research into judgment biases and fallacies. For example, in probabilistic (Bayesian) inference tasks, people often violate some fundamental key properties of classical probability theory. They are prone to ignore base rate probabilities (base-rate neglect; Lu and Nieznański, 2020), to perceive the probability of conjoint events to be more likely than single events (conjunction fallacy; Lu, 2015, 2016), and to regard the outcome of a prior event as having been acknowledged in advance after the event has occurred (hindsight bias; Groß and Bayen, 2021).

Studies assumed that some fallacies and biases happen because, when faced with different types of tasks, many decision makers are liable to use different models with which to construct their preferences (Tversky and Kahneman, 1986). These explanation models can be classified as two kinds: (1) integrative models (compensatory strategies), such as the averaging hypothesis of the conjunction fallacy (Fantino, Kulik, Stolarz-Fantino and Wright, 1997); and (2) heuristic models (non-compensatory strategies), such as the natural frequency hypothesis of the base rate neglect (Gigerenzer and Hoffrage, 1995), the potential surprise hypothesis of the conjunction fallacy (Fisk, 2002), and cognitive reconstruction theories of the hindsight bias (Ash, 2009). Although both integrative and heuristic models are not perfectly rational compared with normative theories, they explain when and why fallacious and biased judgments and decisions appear or disappear. However, research has accumulated considerable evidence supporting heuristic rather than integrative models (see Birnbaum and LaCroix, 2008; Brandstätter, Gigerenzer and Hertwig, 2006; Gigerenzer and Gaissmaier, 2011 for discussions). As the substitution rules to compensate for people's incorrect uses of normative theories, those integrative models assume, for example, expectation rules that people should be competent to the needed quantitative calculation. By contrast, the heuristic models shed light on non-compensatory strategies and propose a bounded rationality perspective on the phenomena. Furthermore, the heuristic models highlight people's fundamental and underlying cognitive processes more closely than the integrative models that emphasize outcome prediction or goodness-of-fit.

While there are different theoretical explanations of biases and fallacies, most of the integrative theories would probably be falsified if they were exposed to thorough testing (even several of them are very unlikely from a psychological point of view). It also appears obviously doubtful that there is a univocal mechanism that fully applies to all the phenomena. There may well be other approaches that reflect underlying mental processes of the phenomena. Besides, some biases and fallacies may be also due to false episodic memories during the judgment process. In what follows in this chapter, we first briefly introduce approaches to decision-making heuristics and episodic memory, with two biases as examples. Then, we present the well-known phenomenon of preference reversals that we will examine in a series of experiments in the subsequent chapters, as well as its theoretical explanations.

1.1. Approaches to decision-making heuristics

The standard paradigm of choice under risk requires people to state their preferences between options by considering well-specified probabilities and payoffs. However, it is common and more realistic that many decision making problems under uncertainty are undertaken either with a lack of probabilities or payoffs or made, especially by naïve decision makers, under ignorance (Kelsey and Quiggin, 1992). In the context of judgment and decision making, certain tasks may be too complex to perform; instead, people adapt some simplified rules of thumb in practice. Since the pioneering idea of bounded rationality was proposed in 1950's, a paradigm shift in the study of human behavior has been taking us to a closer look at real decision makers rather than expected rational beings. There are several critical decision-making heuristics that indicate why fallacies or biases may happen. Different problems would induce people to apply different decision heuristics.

The initial explanation is satisficing theory, a Simon's (1956) semantic work on bounded rationality of choice. The theory highlights the implausibility of the models of rational behavior employed in economics. Simon provided three satisficing principles. First, approximate or simple payoff functions are expected since rational choice models requiring the consideration of all attributes of all the alternatives are incompatible with the access to information and the computational capacities that are actually processed by man. Second, information-gathering processes are costly due to the difficulty of exploration, suggesting an acceptance or reservation value. Partial ordering of payoffs are usually considered since it is difficult to combine attributes of different natures (e.g., probability distribution and payoff) into a complete ordering (an ordering in terms of a weighted sum of payoffs and the cost of alternatives).

Representativeness and availability heuristics ascribe certain anomalies, such as the conjunction fallacy, to people's reliance on some stereotypes or recent events to identify associated characteristics of an object or a person or the likelihood of an outcome occurring (Tversky and Kahneman, 1983). Both the heuristics further suppose that when presented an event with dramatic meanings, people are more deeply appealed by its content and no longer focus on using basic rules to judge probabilities. However, studies have shown opposite opinions against the two heuristics. For example, Gigerenzer and Goldstein (1996) criticized these heuristics as being far too "vague to count as explanations" (p. 593) and "lack theoretical specification" (p. 594). Gavanski and Roskos-Ewoldsen (1991) discovered that representativeness only influences probabilities of single events but not conjunctive events.

An anomalous paradigm linked to boundedly rational behavior is *risk-diversification* heuristic, also known as *naïve diversification*, which stipulates that people allocate equal decision weights to given choice alternatives (Read and Loewenstein, 1995). This heuristic can be regarded as a matter of fact that people adopt the principle of indifference in order to equally distribute their "degrees of favor" among the possible options, rather than consistently choosing the most preferred options in case the payoffs turn out of different than was initially believed. The crux of the idea underlying the heuristic is that a lay person who is averse to unknown probabilities under complete uncertainty seeks to be as close as possible to certainty by minimizing the variance of the expected utility. The heuristic violates traditional accounts of utility maximization and risk minimization.

1.2. Episodic memory

According to the two-component models (Atkinson and Shiffrin, 1968), information is assumed to be processed by a short-term storage system and then to be fed into long-term memory. Short-term memory is also assumed to act as a working memory, a system charging for the temporary maintenance of information demanded by the request of some complex tasks as processing and comprehension. Long-term memory can be further classified as declarative (explicit) memory, the memory that refers to conscious retrieval of facts (semantic) and events (episodic), and non-declarative (implicit) memory, the memory that refers to a heterogeneous collection of abilities whereby experience unconsciously guides behavior without accessing to any memory content (Squire, 1992). Semantic memory is assumed to represent one's knowledge of things at large, for example, knowing the meaning of the word "freedom", how many kilometers there are in a full marathon race, or what is the name of the legendary alien supposedly found in the Roswell incident. By contrast, *episodic memory* is assumed to refer to the capability to recollect an individual event in a certain situation at a certain time (Tulving, 1972), for example, a campfire event on the Baltic seashore last summer, or the title of a presentation in a recent conference one attended.

Tulving (1985) emphasized a necessary correlation between episodic memory and autonoetic (self-knowing) consciousness—the conscious awareness that provides the exceptional characteristic of the experience of remembering from the personal past through the present to a mental time travel to the future. Semantic memory, however, is characterized by noetic (knowing) consciousness. Individuals presumably vary their abilities in possessing and benefiting from autonoetic consciousness. Sometimes people can retrieve information about individually experienced events without autonoetic remembering of the event; instead, they can merely rely on their noetic knowledge to deduce that the event happened. The reason can be that, according to Tulving's (1993) corollary, semantic memory can operate independently of episodic memory, while not vice versa. In other words, people can behave without autonoetic consciousness, but there is no such thing as remembering without knowing. By and large, the overt memory performance is presumably supported by jointly combinations of episodic trace information and semantic retrieval information.

The processes of behavioral judgment and decision making sometimes comprise episodic memory, which involves the retrospective recall of events or episodes that happen in a temporal pattern. Source memory tasks are designed to investigate one of the aspects of episodic memory. *Source memory* refers to the retrieval of contextual details that were acquired incidentally during the prior observation of a remembered item or event (Johnson, Hashtroudi and Lindsay, 1993). Previous research on *source discrimination*, a common paradigm to measure source memory, suggested that during decision-making and judgment processes, some biases and fallacies occur because of false episodic memory, or confabulated memory, which refers to the illusory experience of remembering a past event or episode, but the specific episodic memory never took place (e.g., Lu and Nieznański, 2020; Nakamura and Brainerd, 2017). Conjoint recognition paradigm is used to analyze false episodic memory (Brainerd, Gomes and Nakamura, 2015). In the paradigm, subjects are first presented with a study list containing a set of targets and then respond to a source memory test on which three types of items are administrated: (1) target probes (i.e., old items from the study list), (2) related distractors that share common features of targets, and (3) unrelated distractors. The availability of the memory probe, an item that subjects are asked to recognize whether it was among a series of presented items in a source memory test, can impair the recalled original judgments, leading to a type of memory distortion called *recollection bias* (Erdfelder, Brandt and Bröder, 2007).

Take the hindsight bias for example. In a prototypical source memory design, individuals are first asked to give an unbiased response to particular questions. Then, they receive the correct feedback, and later they have to recall their retrospective answer. As a control, other individuals give their retrospective answer in the absence of feedback instead. In this source discrimination paradigm, it is typically assumed that in the experimental condition, the participants recall their original judgment with the lower probability (i.e., recollection bias). When the original judgment is not recalled, they reconstruct their original judgment to be closer to the correct answers. Blank, Musch and Pohl (2007) indicated that the hindsight bias may be due to false episodic memory that individuals reconstruct when they recall original judgments. Calvillo (2012) found that individuals' recalled judgments are more impaired by feedback when their working memory is loaded by the concurrent task. Further, Calvillo (2013) suggested that an unbiased answer requires responding time for processing, whereas a rapid recall of foresight judgments increases the hindsight bias.

For another example, the base rate neglect refers to a tendency that people are likely to overestimate the conditional probability judgment of a low base rate event when the event is meaningfully related to the condition (Bar-Hillel, 1980). That is, people would assign a higher probability to, say, a professor specializing in musicology than a truck driver if the description they are provided with (e.g., a person who likes to listen to classic music) matches the stereotypes of the former—while paying little attention to the matter of fact that there are much fewer professors of musicology than truck drivers. The base rate neglect is the evidence against the essential standard of Bayes' law, which requires individuals to combine both the knowledge of base rate and the likelihood of observing evidence. In a recent study, Lu and Nieznański (2020) demonstrated that recollection bias can cause the base rate neglect in an episodic memory analogy. More specifically, they designed a source discrimination paradigm, in which subjects were first asked to remember words that were identified by various numerical combinations of color and list during the study phase, and then to respond to questions that analogized episodic memory to the base rate neglect in a source memory test. Results indicated significant deviations between the biased and Bayesian probability judgments (i.e., recollection bias). The findings confirmed evidence that the base rate neglect may be attenuated when individuals are sensitive to relevant congruent sizes of base rate (e.g., the base proportion of professors in musicology) rather than to irrelevant information (e.g., the observing evidence that a person is fond of classic music) at encoding.

1.3. Preference reversal

Prescriptive theories of rational decision making assume that preferences for equivalent tasks are logical, consistent, stable, and exogenous (i.e., affecting evaluations but not being affected by them). However, research in the past half-century has demonstrated an opposite conclusion, showing that preferences are easily influenced by elicitation procedures, subject to monetary payoffs, dependent on contexts, and so on. An ongoing aim within cognitive psychology is to investigate and document how preferences for outcomes are actually constructed in behavioral decision making. Specifically, psychologists and behavioral economists have been intrigued by an anomaly termed choice/reservation-price inconsistency, or the so-called preference reversal (henceforth referred to as PR), first investigated by Lichtenstein and Slovic (1971), Lindman (1971), and Slovic and Lichtenstein (1968). It happens when preferences under different, albeit normatively equivalent, elicitation procedures fail to lead to the same preference ordering. If choice-based and price-based rankings, for example, are viewed as two procedures of preference expression, those who show PR choose a bet or lottery within a direct binary choice task, but at the same time they state a higher certainty equivalent valuation (usually, selling price) for the other bet within a price task.

Thus, PR appears to imply that people may not hold fixed and stable preferences. Instead, they may be reversed when elicitation procedures are shifted from one to another, which is interpreted by psychologists as evidence of context-sensitivity of preferences. Given that preferences are monotone—that is, more wealth or utility is better, incongruous behavior in this sort of gambling game is against most rational theories of decision making such as procedural invariance, the transitivity axiom, and expected utility theory and its generalizations (see Loomes, 1990 for a discussion), which is interpreted by economists as evidence of intransitive preferences. Transitivity requires that an individual who prefers lottery X to lottery Y will both choose X in a straight choice between the two and also express a higher certainty equivalent on X than on Y. Strictly speaking, PR also violates non-expected utility theories, such as prospect theory (Kahneman and Tversky, 1979) and subjectively weighted average utility theory (Karmarkar, 1978), which assume stable preferences across gambles. PR hence poses a serious problem for the normative claims about axiomatic rationality. However, it is not necessarily a challenge that threatens ecological rationality (Berg, 2014).

The anomaly of PR has continually demonstrated its surprising robustness across many variations of the basic experimental paradigm. For example, inconsistencies have been observed in an extremely explicit way, as evidenced by choosing and rejecting the same option (Shafir, 1993); by using simple choice tasks and unforced decisions among experienced buyers (Müller, Kroll and Vogt, 2012); and under rigorous scrutiny (Slovic and Lichtenstein, 1983). Simplification alone by reducing choices to a single pair of gambles seems to be unable to put PR to rest, unless arbitrage is introduced (Chu and Chu, 1990). Even though various conditions, such as instructions and subjects, were controlled as strictly as possible in a series of experiments, Grether and Plott (1979) revealed that PR still persists. PR has also been replicated in both individual and group responses (Mowen and Gentry, 1980; cf., Berga and Moreno, 2020), has been identified in interpersonal comparisons between single and two or more payoffs (Bazerman, Loewenstein and White, 1992), and has been observed more robust than the common consequence effect, or the so-called the Allais paradox, over varying outcome magnitudes (Oliver and Sunstein, 2019).

Although much of the work was largely driven by findings in more artificial experimental settings, PR is also unlikely to disappear in more realistic scenarios such as in incentivized experiments (Grether and Plott, 1979), in real-world markets (Bocquého, Jacquet and Reynaud, 2013; Boothe, Schwartz and Chapman, 2007; Chen, Gao and McFadden, 2020; List, 2002; Lusk, 2019), in real-world lotteries (Ball, Bardsley and Ormerod, 2012; Bohm and Lind, 1993; Kachelmeier and Shehata, 1992; Lichtenstein and Slovic, 1973), in different pricing formats (Berg, Dickhaut and Rietz, 1985), and among highly trained specialists such as bank employees and finance students (Bohm, 1994) as well as economics, business, and medical students (Neumann-Böhme, Lipman, Brouwer and Attema, 2021). PR has also been transcended from the domain of classic monetary lotteries to the ones including, for example, health care decisions (Oliver, 2013; Zikmund-Fisher, Fagerlin and Ubel, 2004), hedonic versus utilitarian goods (e.g. ice cream vs. trash bags; O'Donnell and Evers, 2019), intertemporal choices between smaller-sooner and larger-later options (Gerber and Rohde, 2010), and social distances (Castillo, 2021). Nevertheless, Table 1 summarizes considerable efforts in experimental and field designs that have been made, with some success, to mitigate the robustness of the PR phenomenon.

The lotteries commonly used in laboratory PR experiments have been of three types of design. We hereof refer to them as *gain-zero*, *loss-zero*, and *gain-loss* designs. In the first stage, in a gain-zero design, participants have to choose between two bets with a deliberately wide disparity in their win probabilities and payoffs: (a) a P-bet which has a high probability p_{P} of winning a modest payoff v_{P}^{+} and zero otherwise, and (b) a \$-bet which yields a low to moderate probability $p_{\$}$ of winning a large payoff $v_{\$}^{+}$ and zero otherwise. Similarly, in

Table 1: A list of efforts used in the literature to attenuate PR.

Effort	Study
Exploiting ranking-based, ordinally framed price tasks	Alós-Ferrer et al. (2016)
Using choice list elicitation	Attema and Brouwer (2013); Bostic, Herrnstein and Luce (1990); Neumann-Böhme, Lipman, Brouwer and Attema (2021)
Providing monetary incentives	Berg, Dickhaut and Rietz (2010); Bohm, 1994
Implementing real-world lotteries	Bohm and Lind (1993); Bohm (1994)
Instituting a market-like mechanism	Braga, Humphrey and Starmer (2009); Chai (2005)
Showing in expanded rather than contracted attribute scales	Burson, Larrick and Lynch (2009)
Utilizing nontransparent methods and precise preferences	Butler and Loomes (2007); Pinto-Prades, Sánchez-Martínez, Abellán-Perpiñán and Martínez-Pérez (2018)
Setting arbitrage behavior	Cherry and Shogren (2007); Chu and Chu (1990); Gunnarsson, Shogren and Cherry (2003)
Repeating price auctions	Cox and Grether (1996)
Conducting repeated binary choices to infer certainty equivalent values	Loomes and Pogrebna (2017)
Prompting dialectical thinking	Pang, Keh, Li and Maheswaran (2016)
Holding the join, separate, explicit, or non-explicit evaluation mode constantly	Schmeltzer, Caverni and Warglien (2004)
Inducing sensitivity to risk	Selten, Sadrieh and Abbink (1999)
Presenting in relative frequency instead of probability format	Tunney (2006)
Running multiple-play gambles	Wedell and Böckenholt (1990)

a loss-zero design, participants have to choose between two bets with a deliberately wide disparity in their loss probabilities and payoffs: (a) a P-bet which has a high probability p_{P} of losing a modest payoff v_{P}^{-} and zero otherwise, and (b) a \$-bet which yields a low to moderate probability $p_{\$}$ of losing a large payoff $v_{\$}^{-}$ and zero otherwise.

The two binary bets have an equivalent or roughly similar expected value (EV), that is, the average return that would be expected from repeatedly playing a bet, as indicated by the bet's probability-weighted average of all possible payoffs. Thus, a p_{P} probability of winning $v_{\$}^{+}$, otherwise zero, has an EV of $p_{\mathrm{P}} v_{\$}^{+}$ since $p_{\mathrm{P}}(v_{\$}^{+}) + (1 - p_{\mathrm{P}})(0) = p_{\mathrm{P}} v_{\$}^{+}$. In the second stage, participants have to assign their willingness-to-pay prices, willingness-to-accept prices, or certainty equivalents, respectively from the buyer's, seller's, or neutral viewpoint, to the P-bet and \$-bet. Since subjects ask to accept more when selling a bet than they pay to play when buying, willingness-to-accept prices usually lead to higher valuations than willingness-to-pay prices do (e.g., Birnbaum, Yeary, Luce and Zhao, 2016; Casey, 1994; Hanemann, 1991; Kling, List and Zhao, 2011; Knez and Smith, 1987).

Accordingly, in a gain-loss design, the materials and procedure are the same as those in gain-zero and loss-zero designs, except that the payoffs v_{P}^{-} and $v_{\$}^{-}$ replace the payoff zero in the P-bet and \$-bet, respectively. Table 2 defines the representations of the P-bet and \$-bet and their EVs as well as loss and gain ratios in the three designs. Specifically, a loss or gain ratio is measured by the magnitude of the larger absolute value of the loss or gain payoff divided by the smaller one in a pair of P-bet and \$-bet, namely -$\frac{|v_{\$}^{-}|}{|v_{\mathrm{P}}^{-}|}$, that is, -$\frac{v_{\$}^{-}}{v_{\mathrm{P}}^{-}}$, or $\frac{|v_{\$}^{+}|}{|v_{\mathrm{P}}^{+}|}$, that is, $\frac{v_{\$}^{+}}{v_{\mathrm{P}}^{+}}$, where $v_{\$}^{+} > v_{\mathrm{P}}^{+} > 0 > v_{\mathrm{P}}^{-} > v_{\$}^{-}$, in which we thereof add a minus sign before loss ratios, simply for the purpose of clarifying the cluster of loss ratios from the cluster of gain ratios. It is important to note that we use a relative rather than absolute measure of payoff difference since a difference of \$5 may be perceived as much larger when going from \$5 to

\$10 than when going from \$100 to \$105.

Table 2: The representations of P-bet, \$-bet, EVs, and loss and gain ratios in gain-zero, loss-zero, and gain-loss designs.[a]

Bet/EV/ratio	Gain-zero design	Loss-zero design	Gain-loss design
P-bet	$(p_{\mathrm{P}},\ v_{\mathrm{P}}^{+};\ 1 - p_{\mathrm{P}},\ 0)$	$(p_{\mathrm{P}},\ v_{\mathrm{P}}^{-};\ 1 - p_{\mathrm{P}},\ 0)$	$(p_{\mathrm{P}},\ v_{\mathrm{P}}^{+};\ 1 - p_{\mathrm{P}},\ v_{\mathrm{P}}^{-})$
\$-bet	$(p_{\$},\ v_{\$}^{+};\ 1 - p_{\$},\ 0)$	$(p_{\$},\ v_{\$}^{-};\ 1 - p_{\$},\ 0)$	$(p_{\$},\ v_{\$}^{+};\ 1 - p_{\$},\ v_{\$}^{-})$
$\mathrm{EV}_{\text{P-bet}}$	$p_{\mathrm{P}}v_{\mathrm{P}}^{+}$	$p_{\mathrm{P}}v_{\mathrm{P}}^{-}$	$p_{\mathrm{P}}v_{\mathrm{P}}^{+} + (1 - p_{\mathrm{P}})v_{\mathrm{P}}^{-}$
$\mathrm{EV}_{\text{\$-bet}}$	$p_{\$}v_{\$}^{+}$	$p_{\$}v_{\$}^{-}$	$p_{\$}v_{\$}^{+} + (1 - p_{\$})v_{\$}^{-}$
Loss ratio	N/A	$-\dfrac{v_{\$}^{-}}{v_{\mathrm{P}}^{-}}$	$-\dfrac{v_{\$}^{-}}{v_{\mathrm{P}}^{-}}$
Gain ratio	$\dfrac{v_{\$}^{+}}{v_{\mathrm{P}}^{+}}$	N/A	$\dfrac{v_{\$}^{+}}{v_{\mathrm{P}}^{+}}$

[a] In most of the PR research, the relations of these parameters defined in the P-bet and \$-bet can be specified as follows: (1) $1 > p_{\mathrm{P}} > p_{\$} > 0$, (2) $v_{\$}^{+} > v_{\mathrm{P}}^{+} > 0 > v_{\mathrm{P}}^{-} > v_{\$}^{-}$, and (3) $p_{\mathrm{P}}v_{\mathrm{P}}^{+} + (1 - p_{\mathrm{P}})v_{\mathrm{P}}^{-} =/\approx p_{\$}v_{\$}^{+} + (1 - p_{\$})v_{\$}^{-}$. N/A = not applicable.

Figure 1 shows the payoff structure of the P-bet and \$-bet used in most of the PR research. In the PR literature, other different gambles have also appeared, such as equal-probability gambles being characterized by all payoffs having the same probability, viz., $(\frac{1}{n},\ v_1;\ \frac{1}{n},\ v_2;\ \ldots;\ \frac{1}{n},\ v_n)$ (Ganzach, 1996) and, more generally, multiple-outcome gambles, viz., $(p_1,\ v_1;\ p_2,\ v_2;\ \ldots;\ p_j,\ v_j;\ \ldots;\ p_n,\ v_n)$ (Camacho-Cuena, Seidl and Morone, 2005; Casey, 1991), where $n \geqslant 3$ and $\sum_{j=1}^{n} p_j = 1$, from binary settings introduced earlier.

The choice and/or evaluation between bet pairs, each of which comprises a number of potential monetary payoffs with their specific probabilities, are termed risky decisions (Payne, 1985). Such decisions have been studied either when the probabilities of possible payoffs are expressed explicitly—called description-based tasks—or when we learn the payoffs and their probabilities with the bets through our past experience, called experience-based tasks (Kudryavtsev and Pavlodsky, 2012). Tasks based on description typically tend to focus

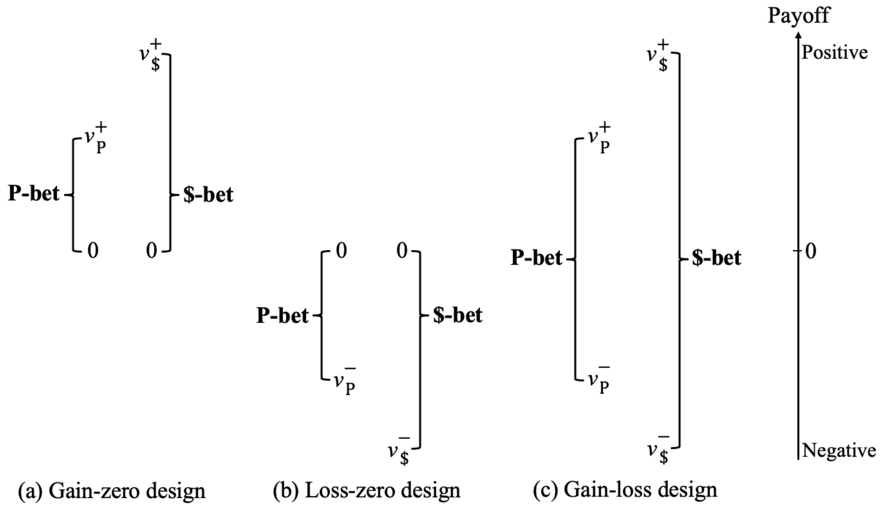


Figure 1: The payoff structure of the P-bet (the safer bet) and $-bet (the riskier bet) in gain-zero, loss-zero, and gain-loss designs.
Note: Risk closely correlates with, and is usually equal to, the variance of the distribution (Baranoff, Brockett and Kahane, 2009). In most of the PR research, the payoffs of $-bet are more extreme than those of the P-bet, that is, $v_\$^+ > v_P^+ > 0 > v_P^- > v_\$^-$, rendering the $-bet payoff-maximizing but riskier than the P-bet; nevertheless, the EVs of the two bets are equal or roughly similar. For the specific payoffs in the current research, see Appendix D.

on one-shot decisions; whereas, tasks based on experience are repeated, and thus decision makers may learn from experience. Although naturally occurring situations often require decision makers to rely on both descriptions and their own experience, it is possible to construct choice tasks purely based on one of them. In the present research, we only analyze behavior in description-based tasks involving gambling bets.

Choice preference is commonly measured by quantifying the proportion of trials in which an alternative is chosen and/or the proportion of people who choose the alternative more often (Shafir, Reich, Tsur, Erev and Lotem, 2008). However, this approach does not provide an isolated measure of risk preferences as those well-established self-reports, such as the German Socio-Economic Panel (Dohmen, Falk, Huffman, Sunde, Schupp and Wagner, 2011) and the Stimulating-Instrumental Risk Inventory (Zaleskiewicz, 2001), usually do. Rather, it reflects a “revealed” preference about the extent of a subject’s underlying risk tolerance.

In related research on PR, since rational theories assuming risk neutrality require that the expected choice proportions relative to the P-bet and \$-bet are equal, preference of safe bets (e.g., P-bets in a gain-zero design) by a risk-neutral individual is interpreted as an underestimation of the Bernoulli parameter p, whereas preference of risky bets (e.g., \$-bets in a gain-zero design) is interpreted as an overestimation of p (Ball, Bardsley and Ormerod, 2012; Brooks and Zank, 2005). It is noteworthy that without this risk-neutral assumption, choice frequencies may diverge from 0.5 and should be independent of probability regardless of risk preference. However, it is widely observed that people fail to averagely allocate their responses to each alternative of paired P-bets and \$-bets, so that their preference tends to be either risk-averse or risk-seeking.

Specifically, inducing risk aversion and seeking builds a strong preference for safe and risky bets, respectively. Nevertheless, extensive evidence has maintained the assumption of stability of risk preferences with a certain degree of freedom on the ground of the possibility of systematic changes (for more recent debates, see Berg, Dickhaut and Rietz, 2013 and Schildberg-Hörisch, 2018). Crucially, accumulated findings suggest that variations in payoffs, incentives, or constraints could not exclusively account for the changes of risk preferences.

Two kinds of PR, often called predicted and unpredicted PR, have been revealed (Cox and Grether, 1996). (Terminology varies in the literature.) Predicted PR happens when a decision maker chooses the P-bet but places a higher value on the \$-bet, whereas unpredicted PR happens when a decision maker chooses the \$-bet but places a higher value on the P-bet. That the former condition is labeled predicted is because this pattern of reversed preferences is systematic (i.e., predominantly unidirectional) and thus cannot be attributed to random error. That the latter condition is labeled unpredicted is because it is hard to rationalize this behavior under any theory of decision making, but might be regarded as a result of carelessness or changes in subjects' strategy. For instance, the cardinal work undertaken by Lichtenstein and Slovic (1971) reported that between 51% and 83% of their respondents showed PR in the predicted direction, but the opposite—unpredicted—PR occurred at a rate of only 6 - 27%. Asymmetry of these two types of PR indicates that choice tasks can elicit different risk preferences than price tasks. However, asymmetric PR becomes even more problematic for economics than does symmetric inconsistency of preference. The reason is that the former could not be interpreted by either normative or positive economics as an effective behavior, whereas the latter could be accommodated in both of the economics by introducing an unbiased random element into choices.

A multitude of studies have indicated several reasons that may determine PR rates. Cox and Epstein (1989) showed that compared with bet pairs which have same or approximately equal EV(s), considerably distinctive EVs may influence predicted and unpredicted PR rates. Johnson, Payne and Bettman (1988) found that probability information displayed in a more complex format increases the frequency of predicted rather than unpredicted PR. Seidl (2002) claimed that the endowment effect often leads non-owners to estimate willingness-to-accept prices higher than willingness-to-pay prices; thus, PR may result from the elicitation of those selling prices. PR also occurs when certainty equivalents are elicited via willingness-to-pay prices, as has been reported by Casey (1991, 1994). Since willingness to accept prices enhance the amount of differential overpricing, thereby it typically leads to more PR than willingness to pay does (e.g., Schmidt and Hey, 2004). It was also observed that the ranking procedure could elicit more unpredicted than predicted PR (e.g., Alós-Ferrer, Granić and Wagner, 2016; Alós-Ferrer, Jaudas and Ritschel, 2021; Bateman, Day, Loomes and Sugden, 2007). There is also evidence that predicted PR is overwhelmingly more often observed than unpredicted PR in those studies with either gain-zero or gain-loss designs (e.g., Chai, 2005; Cubitt, Munro and Starmer, 2004; Kim, Seligman and Kable, 2012; Lichtenstein and Slovic, 1971). In loss-zero designs, predicted PR and unpredicted PR become a mirror reflection—that is, unpredicted PR is more often observed than predicted PR (e.g., MacDonald, Huth and Taube, 1992).

1.4. Theoretical perspectives on PR

Existing explanations of PR generally assume that individuals rely on certain utility theories in their inconsistent value constructions (e.g., Lichtenstein and Slovic, 2006; Payne, Bettman and Johnson, 1992; Sugden, 2003). In the following, we first introduce several related, prevailing or pivotal theories that were put forth to explain the causes of PR, and the fittings of these theories by our data are discussed in the experimental sections.

A prevailing principle that has been put forth to explain why PR is internally logically inconsistent is the violation of the procedural invariance axiom (Tversky, Slovic and Kahneman, 1990; Tversky and Thaler, 1990). It posits that some cardinal elicitation procedures (e.g., choice, price valuation, matching) can affect risk preferences. Particularly, this explanation stipulates that individuals base their actions on salient features of a bet in certain elicitation procedures, while other features could only play a secondary role. For example, when asked about a buying or selling price for the bet, its payoff would come to mind first, while its probability becomes secondarily. It would be until that other appropriate procedures are elicited, then these secondary features might become salient ones. Therefore, preference responses from pricing may be different from those yielded by another elicitation procedure; thus, this inconsistent behavior constitutes a violation of procedural invariance.

Several studies underpinned the above explanation. For instance, Bateman et al. (2007) argued that $-bets tend to be priced higher than their paired P-bets because people often base their decisions on the best (salient) payoffs of the former bets, but fail to adjust sufficiently to take into consideration their other features. Kvam and Busemeyer (2020) proposed a computational model of choice and pricing that assumes an initial bias or anchor that depends on type of price task and a stochastic evaluation accumulation process that depends on bet attributes. The model gives credit to those researchers for the ideas of scale incompatibility (anchoring) and stochastic (error-inclusive) elicitation processes (e.g., Butler and Loomes, 2007; Cubitt et al., 2004; Seidl, 2002) and to Ganzach (1996), despite not referred in their work, for his explanation of PR by anchoring and adjustment. A more recent eye-tracking study indicated that shifts in visual attention toward large monetary payoffs, albeit relative to probabilities, within the price task result in PR (Alós-Ferrer, Jaudas and Ritschel, 2021).

In a similar vein, Tversky, Sattath and Slovic (1988) explained PR as an instance of a general principle of compatibility called "contingent weighting", such that attribute weights are sensitive to how preferences are elicited. Particularly, the weighting of an input is enhanced by its compatibility with the output. On the one hand, individuals adopt a lexicographic strategy within qualitative or ordinal tasks like choice, whereby the most compatible input is an ordering of options based on the most important attribute. On the other hand, individuals adopt a quantitative strategy within quantitative tasks like pricing, whereby the most compatible inputs are relevant numeric assessments of the attributes of the options. In each case, either the most important attribute or relevant numeric attributes loom larger than the others. More recently, Catapano, Shennib and Levav (2022) put forward the contingent weighting model to explain PR between digital goods being preferred in choice and their physical equivalents being preferred relatively more in willingness to pay.

In addition to establishing the empirical evidence for PR, Kahneman and Tversky (1979) also proposed the most influential account of its psychological origin—prospect theory—as a compensatory way to integrate probabilities and payoffs in a given prospect. According to the theory's successor—cumulative prospect theory (Tversky and Kahneman, 1992), people do not tend to evaluate outcomes as absolute amounts, as expected utility assumes. Instead, they overestimate small probability outcomes and underweight middle and high probability outcomes, relative to the actual likelihood of occurrence. People also evaluate gains or losses on a two-component value function featuring rank-dependent decision weights, such that losses loom about twice larger than gains psychologically, dependent on their distances from the initial reference position, often the *status quo*, and that position itself. According to cumulative prospect theory, the value function $u(v)$ for a gain, zero, or loss payoff v is defined by

$$u(v) = \begin{cases} f(v), & \text{if } v > 0 \\ 0, & \text{if } v = 0 \\ \lambda g(v), & \text{if } v < 0, \end{cases} \tag{1}$$

where λ is a loss aversion coefficient describing subjects' fear from losses, and $f(v)$ and $g(v)$ are further defined as follows:

$$f(v) = \begin{cases} v^{\alpha}, & \text{if } \alpha > 0 \\ ln(v), & \text{if } \alpha = 0 \\ 1 - (1+v)^{\alpha}, & \text{if } \alpha < 0, \end{cases} \tag{2}$$

and

$$g(v) = \begin{cases} -(-v)^{\beta}, & \text{if } \beta > 0 \\ -ln(-v), & \text{if } \beta = 0 \\ (1-v)^{\beta} - 1, & \text{if } \beta < 0, \end{cases} \tag{3}$$

where the parameter α and β capture the shape of the value function.

The weighting function $w(p)$ in a given probability p whereby the payoff v occurs is defined by

$$w(p) = \frac{p^{\gamma}}{[p^{\gamma} + (1-p)^{\gamma}]^{(1/\gamma)}}, \tag{4}$$

where the parameter γ captures the shape of the weighting function. The combination of specific curvature of the probability weighting function, kinked utility function, and reference points allows (cumulative) prospect theory to model risk preferences (cf., Appendix I).

In the perspective of the reference-dependent generalization of subjective expected utility theory (Sugden, 2003), in which reference dependence (a reference point) refers to the tendency to evaluate outcomes as gains or losses, rather than in terms of net assets, PR needs not be interpreted as an inconsistency. This is because the theory assumes that the decision maker is given no endowment within a choice task, but is endowed with one of the P-bet and \$-bet within a price task. As a result, within the choice task, the decision maker shows her preference from a view of a reference point in which she owns neither of the bets. Within the price task, she expresses her preferences, as indirectly revealed by evaluating the two bets' willingness-to-accept prices, from a view of a reference point in which she owns one of the bets (i.e., a fixed reference point; see Bleichrodt, 2009 for a model with shifting reference points). Crucially, the decision maker's risk preferences need not be consistent across these tasks because of different reference points from which the relevant gain or loss outcomes of the P-bet and \$-bet are viewed.

Furthermore, the Sugden's (2003) theory criticizes Kahneman and Tversky's (1979) prospect theory for not being applicable to situations in which the probability distributions of gains and losses cannot exchange from one bet to another, due to an undefined state of the world where the decision maker's initial status quo is itself uncertain. Remarkably, Sugden (2003) introduced the notions of exchange-averse and -loving, referring to the decision maker's attitudes towards a preference to the status quo and other options, respectively. Then, the theory posits that predicted PR occurs largely because of strictly concave utility functions compatible with exchange aversion.

The value encoding account (Payne, 1982; Payne, Bettman and Johnson, 1992) states that loss aversion, a phenomenon referring to weighting losses more than equivalent-sized gains, is extensively expected to occur within choice tasks (i.e., the so-called encoding stage) and not within price or rating tasks. According to McGraw, Larsen, Kahneman and Schkade (2010) who proposed a similar explanation, choice tasks enable people to compare the different valences of gain and loss simultaneously, whereas price tasks compel people to evaluate the different valences separately, namely, to evaluate the payoff only relative to other payoffs with the same valence (e.g., they consider losses against other losses). It is tempting to speculate that when asked to *choose* among bets with both gain and loss payoffs, loss aversion is likely to happen because people probably place great emphasis on losses over gains due to differential weighting systems according to the loss attention account (Yechiam and Hochman, 2013). However, when asked to *price* a pair of P-bet and \$-bet with both gain and loss payoffs, it is natural to compare the gain of the P-bet relative to that of the \$-bet, and the loss of the P-bet relative to that of the \$-bet.

A growing variety of studies have shown another elicitation effect, namely preference shifts in *joint* versus *separate* evaluation. As the terms indicate, joint evaluation refers to situations in which multiple options are presented and evaluated simultaneously, while separate evaluation refers to situations in which multiple options are presented and evaluated at different times. Individuals may prefer one option more than the other in separate evaluation, but prefer it less in joint evaluation, giving rise to PR. Among these theories accounting for divergences between the two evaluations, the evaluability hypothesis predicts an attribute importance effect (Hsee, 1996; Hsee, Loewenstein, Blount and Bazerman, 1999; Tyszka and Zaleskiewicz, 2006). That is, for options with multiple attributes, the attribute that is relatively more difficult to evaluate independently receives greater weight when the options are presented jointly. Accumulated evidence also showed that (1) negative attributes weigh more in separate than joint evaluation (Willemsen and Keren, 2004); (2) objectively worse options are found more preferential in separate than in joint evaluation (Semaan, Gould, Chao and Grein, 2019; Sevdalis and Harvey, 2006); and (3) $-bets (or P-bets) are preferred in separate (or joint) evaluation within both choice and price tasks—that is, PR is attenuated when the evaluation mode is held constantly (Schmeltzer et al., 2004).

While studies also explained the PR phenomenon from more than one variant of the heuristic models, the essence of most of them is that the choice and price tasks bring somehow different cognitive processes into play. For example, Schwartz (2003) showed that choice evokes qualitative heuristics. In a shopping setting with consumer products as stimuli, Boothe et al. (2007) found that decision makers use a market value heuristic—essentially, a type of the availability heuristic—wherein when they are unsure of how to translate their preference onto a dollar scale, they substitute the product's retail price as the basis of their pricing evaluations. In an unpublished thesis, Maxwell (1992) revealed that when facing with difficult tasks, decision makers may resort to an effort-saving heuristic by removing selling prices that violate certain constraints. As a result, they may be not willing to assign a minimum selling price that is negative or exceed the market price, even if such a selling price reflects their preference.

Further, O'Donnell and Evers (2019) showed that when choice options are common and not very valuable goods, consumers are more likely to rely on an affect-based heuristic as a fast and low-risk approach to make simple choices, such that they prefer affective to functional goods in choices as opposed to decisions elicited by willingness-to-pay. The affect-based heuristic is characterized by subjects' reliance on an affective state (with or without consciousness) that enables one to distinguish between a positive or negative quality of a stimulus (Slovic, Finucane, Peters and MacGregor, 2002). In a psychophysics paradigm called salience driven value integration, Tsetsos, Chater and Usher (2012) argued that people have an already established ability to integrate emotional affect with rewards in numerosity judgment. Choices may be distorted by differential weighting applied on the salient sampled values.

1.5. Outline of substantive sections

The rest of the thesis is organized as follows. In Section 2 we propose our hypotheses on the basis of empirical and theoretical literature regarding risk preferences, loss aversion, magnitude effects of PR, heuristic-based binary choices, context effects, and episodic memory. In particular, a new framework among three classes of fast-and-frugal heuristics is developed to lay the groundwork for explaining preferential choice decisions in PR. Section 3 gives a brief overview of the key experiments that are described in more detail in the following sections. Section 4 presents the relevant statistical tests that were used in the analysis of our data.

From Section 5 to Section 9, we describe five experimental or meta-analytic designs, research approach, empirical tests, and results with five key objectives. One is to test magnitude effects in PR using the classic two-task design. Another is to test the explanations of the three heuristics and another existing psychological hypothesis on choice decisions in PR, with tight controls for loss ratios of bet pairs. A third is to test the impact of expected value difference (EVD) on classic PR and contextual PR. A fourth is to test episodic memory in classic and contextual PR. The rest is to conduct meta-analyses on binary choice and predicted and unpredicted PR in order to further examine whether our hypotheses fit the data pattern. These objectives are achieved by novel combinations of experimental design features which we explain in the method section of each experiment. While Section 10 provides a general discussion of PR in our experiments, Section 11 summarizes the main findings and limitations of this research and possible future avenues. Section 12 draws a final conclusion.

Appendix A and Appendix B describe formal frameworks of the loss-averse rule and the majority rule, respectively. Appendix C presents formal definitions of propositions and conjectures and their proofs. Appendix D contains complete lists of all lottery pairs used in our experiments. Appendix E shows experimental instructions and material illustrations. From Appendix F to Appendix H, we report some supplementary descriptive and statistical analyses in detail. Appendix I discusses the play-out and payment effects on different patterns of PR and price valuations against alternative benchmark theories of risky decision making across our experimental treatments.

2. Hypotheses

2.1. Risk preferences and magnitude effects

Previous studies of decisions based on description have shown different patterns of risk preferences with different PR designs. First, when gain-zero designs were employed, it seems that the payoff variance between the P-bet and \$-bet can determine the pattern. More precisely, on the one hand, if the gain ratios of bet pairs, $\frac{v_\$^+}{v_P^+}$, were no more than 6.0, subjects were more likely to choose the safer P-bet—and less to choose the riskier \$-bet (e.g., Ball et al., 2012; Butler and Loomes, 2007; Edwards, 1954; Zhang, 1999), though see Zhang (1998) for evidence that the reverse may occur. On the other hand, if the gain ratios of bet pairs were no less than 20.0, subjects were more likely to choose the riskier \$-bet—and less to choose the safer P-bet (e.g., Chang, Wang and Yin, 2011; Zhang, 1999).

Second, there has been relatively rare evidence accumulated regarding risk preference in loss-zero designs. Third, when gain-loss designs were employed, however, the pattern is much more mixed. On the one hand, if the loss ratios of bet pairs, $-\frac{v_\$^-}{v_P^-}$, were no more than -3.0, some studies observed their subjects being more likely to choose the P-bet—and less to choose the \$-bet (e.g., Cox and Grether, 1996); some found that the pattern was the other way around (e.g., Grether and Plott, 1979); while others showed no significant differences (e.g., Lichtenstein and Slovic, 1971). On the other hand, if the loss ratios of bet pairs were no less than -3.0, it seems that larger loss ratios tend to induce subjects to choose the P-bet due to risk aversion—an assumption for which little empirical evidence exists. Thus, it has been shown that the inclusion of positive and/or negative payoffs in gambles can influence behavior in a variety of ways.

While different methods of eliciting those preferences can produce substantially conflicting results, it is important to understand the processes people are using to produce their responses. We will discuss some potential determinants that might result in various patterns of risk preferences in Section 5.3.1 Risk preference. More generally, risk preferences have been found more unstable within choice than price tasks, as evidenced by overestimating $-bet within price tasks as a prominent observation in PR (e.g., Cox and Grether, 1996; Tversky et al., 1990). A meta-analytic overview of the experimental designs can be found in Section 9 Binary choice and PR: Three meta-analyses; design details are in the original papers.

These results above indicate that risk preferences within choice tasks of PR experiments are susceptible to the relative magnitude size (i.e., a discount rate declining with the amount at stake) of loss payoffs between the P-bet and $-bet in a given bet pair (Fehr-Duda, Bruhin, Epper and Schubert, 2010; Vanunu, Pachur and Usher, 2019). The motivation for the experiments presented here was based on the idea that how people judge magnitudes of payoff in PR may be analogous to empirical evidence found in psychophysics. Several lines of psychophysical research show magnitude effects. First, changes in stimulus size influence modulation degrees of affective judgments (De Cesarei and Codispoti, 2006) and autonomic responses (Reeves, Lang, Kim and Tatar, 1999). Second, the number of stimulus categories affects judgmental accuracy of loudness (Garner, 1953; cf., Garner, 1954). Third, perceptual judgments depend upon relative rather than absolute magnitude information (Laming, 1984, 1997). Fourth, subjects compare stimuli with a set of category limens (Parducci, 1965; cf., Parducci, Knobel and Thomas, 1976). Fifth, risky choices are heavily affected by accompanying prospects available (Stewart, Chater, Stott and Reimers, 2003).

In PR research, limited studies to date regarding magnitude effects have merely considered risk preferences within gain-zero designs only. More specifically, Bocquého et al. (2013)

used multiple rewards and time delay to elicit long-term time preferences. Contrary to the assumption of a time-consistent preference by the standard discounted utility model of economics, temporal PR occurs when a subject prefers receiving a smaller-sooner reward to a larger-later reward or vice versa, but reverses preferences when both rewards are delayed by a common period of time. However, the results indicated that discount rates at which temporal PR is determined show no clear evidence of the usual magnitude effect.

Further, Zeng, Xiong, Hou, Chen and Su (2021) discovered that subjects with the A/A genotype exhibit stronger PR than others when gain ratios are large. Oliver and Sunstein (2019) varied payoff sizes of possible gains at the same synchronized rates, such as from large outcomes of P-bet = (0.8, £1,000,000) and \$-bet = (0.2, £4,000,000), to moderate outcomes of P-bet = (0.8, £10,000) and \$-bet = (0.2, £40,000), and to small outcomes of P-bet = (0.8, £100) and \$-bet = (0.2, £400). The results also suggested that risk preferences are not dependent on outcome magnitude. Nevertheless, Kwong and Wong (2006) (see also Wong and Kwong, 2005) demonstrated that the framing effect of ratio size can result in PR, with equivalent numerical information being expressed in a small ratio (e.g., $\frac{99.99\%}{99.997\%}$ in reliability) compared to a large ratio (e.g., $\frac{0.01\%}{0.003\%}$ in failure rate).

All together, these PR studies did not manipulate payoff magnitudes progressively, such as from small to relatively large rates between possible payoffs of bet pairs, nor did they examine the magnitude effect of payoff in a gain-loss design. Thus, it remains unclear whether the relative distinction of the loss or gain payoff between the P-bet and \$-bet in a given bet pair as opposed to their absolute magnitudes influences risk preferences. Taking into account loss aversion and the aforementioned instability of risk preference within choice rather than price tasks, we propose the following two hypotheses:

Hypothesis 1.a. When bet pairs have low loss ratios, individuals will be more risk-seeking, as evidenced by choosing \$-bets over P-bets.

Hypothesis 1.b. When bet pairs have high loss ratios, individuals will be more risk-averse, as evidenced by choosing P-bets over \$-bets.

It seems that, on the one hand, a low loss ratio of the P-bet and \$-bet in a given bet pair tends to induce less predicted but more unpredicted PR because the \$-bet is likely to be chosen but underpriced. On the other hand, a high loss ratio of the P-bet and \$-bet in a given bet pair tends to induce more predicted but less unpredicted PR because the P-bet is likely to be chosen, while the \$-bet is likely to be overpriced. We will review a number of factors that influence the degree of PR in Section 5.3.2 Predicted and unpredicted PR. We first propose the following two hypotheses:

Hypothesis 2.a. Individuals will reveal less predicted PR when bet pairs have low than high loss ratios.

Hypothesis 2.b. Individuals will reveal more unpredicted PR when bet pairs have low than high loss ratios.

2.2. Heuristic-based binary choice: Explanations by the loss-averse rule, the majority rule, and the equate-to-differentiate rule

Which underlying judgment processes do individuals undertake to make decisions within choice tasks of PR? And whether there exist any conventional normative descriptions of human decision making within these tasks? We may challenge these questions by assuming that people implement optimal or heuristic strategies by which they make decisions under risk, an example of strategy selection (Gigerenzer, 2008; Lieder and Griffiths, 2017). Most theories of strategy selection assume a context-sensitive judgment process, in that people are able to assess the usefulness of a strategy that could be deployed to perform a given task, on the basis of asymmetric gain-loss valuation (Kahneman and Tversky, 1979; O'Brien and Ahmed, 2019), the strategy's applicability in a particular domain (Kolodner, 1993), and/or the magnitude of information quality and punishment (Kvam and Hintze, 2018). All these strategies require, either explicitly or implicitly, certain inferential criteria.

Provoked by the choice environment of PR which needs to generate specific and quantitative predictions, we posit that individuals may use, among others, three different heuristic strategies. As introduced in Section 1.1 Approaches to decision-making heuristics, research in psychology has demonstrated that individuals often heuristically rely on "first impressions" when making choice decisions. Compared to the rational theories proposing that choice judgments are based on a process of integrating an alternative's attribute payoffs and probabilities into an EV like calculation, as proposed by expected utility models such as cumulative prospect theory, all the three heuristic strategies presume that people make comparisons of alternatives on attended attributes.

Only recently have such attribute-wise comparisons in choice judgments been confirmed by eye-tracking research (Kim et al., 2012; Meißner, Musalem and Huber, 2016; Yegoryan, Guhl and Klapper, 2020), supporting "satisficing" heuristic strategies of bounded rationality which serve as some shortcut or simplification due to cognitive capacity limitations or in order to make the decision faster or more easily (Simon, 1957). In sum, the use of heuristic strategies or rule of thumb has been largely supported and also sometimes found better than normative decision theories for modeling fundamental and underlying cognitive processes (see Lu, 2016 for a discussion).

The first strategy is the so-called loss-averse rule, a novel framework that we provide to measure and identify choice comparisons. Instead of a domain-*general* inference algorithm, such as expected utility theory, that treats gain and loss payoffs in a given bet equally, or a domain-*specified* account, such as accumulative prospect theory, that features the increased subjective weight of losses compared with equivalent gains, the loss-averse rule is based on a simply domain-*exclusive* idea that regards losses as most important for reaching a decision and that other information is ignored. The rule puts emphasis on losses rather than gains or probabilities because the interrelated concepts of loss aversion with respect to neutral risk preference or status quo imply that individuals are especially prone to limit their exposure to losses. While in some cases loss aversion leads to suboptimal decisions, in many situations it is an adaptive strategy.

More concretely, the criterion of the loss-averse rule presumes that loss aversion in binary choices will be likely to occur in the precondition in which the loss ratio of the P-bet and \$-bet in a given lottery, namely $-\frac{v_{\$}^{-}}{v_{\mathrm{P}}^{-}}$, where $0 > v_{\mathrm{P}}^{-} \geqslant v_{\$}^{-}$ (cf., Table 2), reaches a level of threshold $-t$. If this precondition occurs, a decision maker is likely to choose the bet that has the smaller absolute value of loss payoff, that is, to choose the P-bet rather than the \$-bet owing to $-\frac{v_{\$}^{-}}{v_{\mathrm{P}}^{-}} \geqslant -t$ and $|v_{\$}^{-}| > |v_{\mathrm{P}}^{-}|$. A loss ratio, being any number less than the level of threshold, indicates that a decision maker does not prioritize loss aversion as the uttermost criterion in choice judgments, such that random responses might be expected when there is no objectively optimal option. If this precondition occurs, the decision maker stochastically chooses the P-bet or \$-bet.

Crucially, this threshold-unalarmed circumstance has been convincingly illuminated in both the psychological and economic literature, as supported by the findings of excessive variability (e.g., Friedman and Massaro, 1998), perceptual noise (e.g., Shafir et al., 2008), and preference imprecision (e.g., Bayrak and Hey, 2020) in the context of decision making. The loss-averse rule can be categorized as a type of the well-known take-the-best heuristic, a one-reason shortcut according to which judgments are based on a single "good" reason only, and other cues are ignored (Gigerenzer and Gaissmaier, 2011). We provide a formal description of the loss-averse rule in Appendix A.

In particular, we carried out one experiment involving a battery of choices between binary bet pairs, and compared the prediction power of cumulative prospect theory, the loss-averse rule, and another two non-compensatory heuristic strategies (outlined below) for explaining and predicting subjects' choices in individual decision making. For cumulative prospect theory, we compute the parameters by following Tversky and Kahneman (1992). For the three intuitive heuristics, we test them directly according to their decision criteria. Thus, we propose the following hypothesis:

Hypothesis 3. When the loss ratio of a pair of P-bet and $-bet exceeds its threshold, individuals will be more likely to use the loss-averse rule or cumulative prospect theory than the other decision strategies (e.g., the majority rule, outlined below), as evidenced by choosing the bet that has the smaller absolute value of loss payoff. By contrast, when the loss ratio does not exceed its threshold, individuals will use decision strategies at random.

The other two strategies are the majority rule (Zhang, Hsee and Xiao, 2006) and the equate-to-differentiate rule (Li, 2004). The former posits that individuals prefer to choose the majority-weakly-superior option (i.e., slightly more favorable on most of its attributes) than the minority-strongly-superior option (i.e., considerably more favorable on few of its attributes). We provide a formal description of the majority rule in Appendix B (cf., May, 1952 for the pioneering axiomatic characterization of the rule). The latter, instead, postulates that individuals regard one or several smaller different attributes of options as being equivalent with each other and then leave the most distinct attribute as the determinant of the final pairwise choice. That is, individuals prefer to choose, according to the majority rule's classification, the minority-strongly-superior option based on approximate estimation.

Therefore, the two rules may predict congruent or contradictory choice preferences for multi-attribute options. Nevertheless, the main point of both of these two contrasting rules is, in the case of pairwise choice, to detect dominance distinctions between different attributes of options. Moreover, individuals are not likely to price or match an option as dominated by the most prominent attribute, since it is more difficult to identify a "majority" or a "differentia" when these response modes are elicited. Instead, we suppose that individuals are more apt to use both the rules in choice in preference to the other elicitation procedures.

A considerable amount of research on the underlying process of individual decision making provided credible findings in favor of both the majority rule (e.g., Dasgupta and Maskin, 2008; Lu and Nieznański, 2017) and the equate-to-differentiate rule (e.g., Lu, 2016). Recently, both the rules have drawn much attention in an academic conference about the aggregation or distinction of behavioral judgments between binary, weak-dominant multi-attribute options (see Lu, 2016). Specifically, Birnbaum and Diecidue (2015) gave insight into how their participants manifested PR when being assumed to use the majority rule. By contrast, Li (2006) shed light on how the equate-to-differentiate rule can explain the occurrence of PR within matching and pricing tasks, but theoretically presumed that individuals regard loss rather than gain domains as the most distinct attribute within choice tasks. That is, individuals tend to avoid choosing a \$-bet since it pertains to the worst possibility to lose a large payoff—hence, seemingly loss aversion within choice tasks. However, previous research neither examined the obviously diverging predictions between the alternative rules, nor analyzed the conditions under which individuals may be likely to use one or another when choosing between weak-dominant pairwise options. Next, we align the possibly congruent and contradictory predictions by the two rules.

In Figure 2 we illustrate a choice task between a P-bet = (p_{P}, v_{P}^{+}; 1 - p_{P}, v_{P}^{-}) and a \$-bet = ($p_{\$}$, $v_{\$}^{+}$; 1 - $p_{\$}$, $v_{\$}^{-}$) differing in three attributes (probability, gain, and loss), where, by definition, $1 > p_{\mathrm{P}} > p_{\$} > 0$. For simplicity, we define the relations between the payoffs v_{P}^{+} and $v_{\$}^{+}$ and between the payoffs v_{P}^{-} and $v_{\$}^{-}$ more generally in the current section as well as in Experiment 2: Binary choices in PR, namely $v_{\mathrm{P}}^{+}, v_{\$}^{+} > 0 > v_{\mathrm{P}}^{-}, v_{\$}^{-}$, instead of the more strict ones that were confined in Figure 1 and Experiment 1: Magnitude effects in PR, namely $v_{\$}^{+} > v_{\mathrm{P}}^{+} > 0 > v_{\mathrm{P}}^{-} > v_{\$}^{-}$.

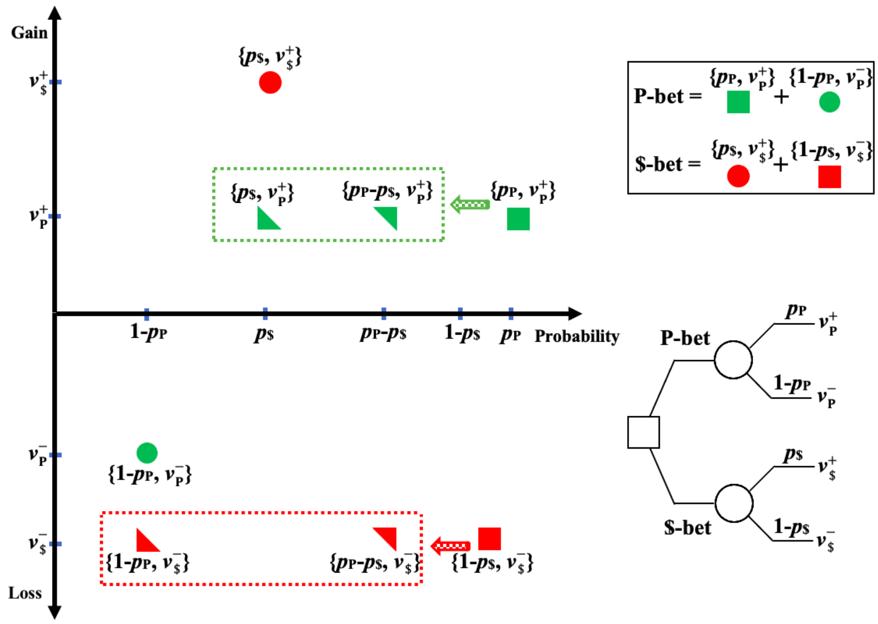


Figure 2: A choice task between a P-bet and a \$-bet.
Note: The components of the P-bet and \$-bet are placed in colors green and red, respectively. The example illustrates the magnitudes of the gain and loss attributes in such an order: $v_{\$}^{+} > v_{\mathrm{P}}^{+} > 0 > v_{\mathrm{P}}^{-} > v_{\$}^{-}$.

Both Zhang et al. (2006) and Li (2004) indicated that individuals are more likely to use the respective rules when encouraged to compare one attribute after another (i.e., intra-attribute comparison), as opposed to taking all the attributes of an option into account simultaneously (i.e., intra-option integration). Moreover, past studies provided support for the hypotheses that the use of the principle of decomposition can contribute to make better judgments (Armstrong, Denniston and Gordon, 1975; Kleinmuntz, 1990). Therefore, we suppose that first, a decision maker uses either the majority rule or the equate-to-differentiate rule, thus decomposing each of the bets into two components, namely $\{p_{\text{P}}, v_{\text{P}}^{+}\}$ and $\{1 - p_{\text{P}}, v_{\text{P}}^{-}\}$ from the P-bet, and $\{p_{\$}, v_{\$}^{+}\}$ and $\{1 - p_{\$}, v_{\$}^{-}\}$ from the \$-bet. Next, the decision maker decomposes $\{p_{\text{P}}, v_{\text{P}}^{+}\}$ into $\{p_{\$}, v_{\text{P}}^{+}\}$ and $\{p_{\text{P}} - p_{\$}, v_{\text{P}}^{+}\}$, and decomposes $\{1 - p_{\$}, v_{\$}^{-}\}$ into $\{1 - p_{\text{P}}, v_{\$}^{-}\}$ and $\{p_{\text{P}} - p_{\$}, v_{\$}^{-}\}$. Then, the decision maker judges between a P-bet = $(p_{\$}, v_{\text{P}}^{+}; p_{\text{P}} - p_{\$}, v_{\text{P}}^{+}; 1 - p_{\text{P}}, v_{\text{P}}^{-})$ and a \$-bet = $(p_{\$}, v_{\$}^{+}; p_{\text{P}} - p_{\$}, v_{\$}^{-}; 1 - p_{\text{P}}, v_{\$}^{-})$, which yields the same probabilities for each two corresponding components, that is, $p_{\$}$ for $\{p_{\$}, v_{\text{P}}^{+}\}$ and $\{p_{\$}, v_{\$}^{+}\}$, $p_{\text{P}} - p_{\$}$ for $\{p_{\text{P}} - p_{\$}, v_{\text{P}}^{+}\}$ and $\{p_{\text{P}} - p_{\$}, v_{\$}^{-}\}$, and $1 - p_{\text{P}}$ for $\{1 - p_{\text{P}}, v_{\text{P}}^{-}\}$ and $\{1 - p_{\text{P}}, v_{\$}^{-}\}$.

Critically, empirical research has indicated the primacy of outcome overriding probability (e.g., Brandstätter et al., 2006; Huber, 2007; Lang and Betsch, 2018; Loewenstein, Weber, Hsee and Welch, 2001; Lu and Nieznański, 2020; Robinson and Botzen, 2019; Sunstein, 2003; Suter, Pachur and Hertwig, 2016). More recent evidence of PR showed that (1) human subjects do not use probabilistic information precisely (Bayrak and Hey, 2017); and (2) when options with certainty are linearly spaced and evenly distributed around the EV of another alternative risky option, ranges of probability do not influence respondents' preferences for this risky option anymore (Kusev, van Schaik, Martin, Hall and Johansson, 2020; see also Lichtenstein and Slovic, 1971). Animals such as pigeons and rats too show suboptimal choice behavior by neglecting probability (e.g., Stagner and Zentall, 2010; Zentall, Smith and Beckmann, 2019). Thus, we presume that the decision maker equates the attribute of probabilities of the P-bet with that of the \$-bet, then judging the two bets by comparing their payoffs alone among three paired components, namely v_{P}^{+} versus $v_{\$}^{+}$, v_{P}^{+} versus $v_{\$}^{-}$, and v_{P}^{-} versus $v_{\$}^{-}$.

Table 3 shows two-stage comparisons of these three paired components on the basis of seven exclusive conditions. Take the condition No. 3, where $v_\$^+ > v_P^+$, $v_P^+ > v_\$^-$, and $v_P^- = v_\$^-$, as an example. The decision maker will filter the latter two equivalent payoffs, namely v_P^- versus $v_\$^-$, in the ①st stage. Then, the decision maker will choose the bet which dominates a more distinct attribute payoff between $v_\$^+$ - v_P^+ and v_P^+ - $v_\$^-$ in the ②nd stage, by any of the two rules. That is, the decision maker will either choose the P-bet if the inequality v_P^+ - $v_\$^-$ > $v_\$^+$ - v_P^+ is held (Proposition 3.1), as exemplified by such a bet pair as P-bet = (60%, 15; 40%, -19) and \$-bet = (40%, 32; 60%, -19), where v_P^+ - $v_\$^-$ = 15 - (-19) = 34 > $v_\$^+$ - v_P^+ = 32 - 15 = 17; or choose the \$-bet if the inequality $v_\$^+$ - v_P^+ > v_P^+ - $v_\$^-$ is held (Proposition 3.2), as exemplified by such a bet pair as P-bet = (75%, 15; 25%, -12) and \$-bet = (25%, 71; 75%, -12), where $v_\$^+$ - v_P^+ = 71 - 15 = 56 > v_P^+ - $v_\$^-$ = 15 - (-12) = 27.

Consider another condition No. 5, where $v_\$^+ > v_P^+$, $v_P^+ > v_\$^-$, and $v_\$^+ > v_\$^-$. If using the majority rule, the decision maker will choose the P-bet in the ①st stage and will stop any further examination in the ②st stage, as exemplified by such a bet pair as P-bet = (75%, 5; 25%, -3) and \$-bet = (25%, 30; 75%, -6), where $v_\$^+$ = 30 > v_P^+ = 5, v_P^+ = 5 > $v_\$^-$ = -6, and v_P^- = -3 > $v_\$^-$ = -6. Alternatively, if using the equate-to-differentiate rule, the decision maker will choose the bet which dominates the most distinct attribute payoff among $v_\$^+$ - v_P^+, v_P^+ - $v_\$^-$, and v_P^- - $v_\$^-$ in the ②nd stage. That is, the decision maker will either choose the \$-bet if the inequalities $v_\$^+$ - v_P^+ > v_P^+ - $v_\$^-$ and $v_\$^+$ - v_P^+ > v_P^- - $v_\$^-$ are held (Conjecture 5.1), as exemplified by the previous bet pair, where $v_\$^+$ - v_P^+ = 30 - 5 = 25 > v_P^+ - $v_\$^-$ = 5 - (-6) = 11 and $v_\$^+$ - v_P^+ = 25 > v_P^- - $v_\$^-$ = -3 - (-6) = 3; or choose the P-bet if the inequalities v_P^+ - $v_\$^-$ > $v_\$^+$ - v_P^+ and v_P^+ - $v_\$^-$ > v_P^- - $v_\$^-$ are held (Conjecture 5.2), as exemplified by such a bet pair as P-bet = (60%, 10; 40%, -3) and \$-bet = (40%, 30; 60%, -12), where v_P^+ - $v_\$^-$ = 10 - (-12) = 22 > $v_\$^+$ - v_P^+ = 30 - 10 = 20 and v_P^+ - $v_\$^-$ = 22 > v_P^- - $v_\$^-$ = -3 - (-12) = 9.

In summary, it is important to note that the decision maker applies a stopping rule after

Table 3: Choice preferences predicted by the majority rule and the equate-to-differentiate rule, according to the two-stage payoff comparisons.

	①st-stage comparison				②nd-stage comparison (if needed)	Prediction[a]			Proposition or Conjecture
No.	v_{P}^{+} vs. $v_{\$}^{+}$	v_{P}^{+} vs. $v_{\$}^{-}$	v_{P}^{-} vs. $v_{\$}^{-}$	Division		Majority	Equate	Inequality[b]	
1	$v_{\mathrm{P}}^{+} = v_{\$}^{+}$	$v_{\mathrm{P}}^{+} > v_{\$}^{-}$	$v_{\$}^{-} > v_{\mathrm{P}}^{-}$	↗	$v_{\$}^{-}$ - v_{P}^{-} > v_{P}^{+} - $v_{\$}^{-}$	\$-bet ②	\$-bet ②	True	1.1
				↘	v_{P}^{+} - $v_{\$}^{-}$ > $v_{\$}^{-}$ - v_{P}^{-}	P-bet ②	P-bet ②	True	1.2
2	$v_{\mathrm{P}}^{+} = v_{\$}^{+}$	$v_{\mathrm{P}}^{+} > v_{\$}^{-}$	$v_{\mathrm{P}}^{-} \geqslant v_{\$}^{-}$	→		P-bet ①	P-bet ①	False	2
3	$v_{\$}^{+} > v_{\mathrm{P}}^{+}$	$v_{\mathrm{P}}^{+} > v_{\$}^{-}$	$v_{\mathrm{P}}^{-} = v_{\$}^{-}$	↗	v_{P}^{+} - $v_{\$}^{-}$ > $v_{\$}^{+}$ - v_{P}^{+}	P-bet ②	P-bet ②	True	3.1
				→	$v_{\$}^{+}$ - v_{P}^{+} > v_{P}^{+} - $v_{\$}^{-}$	\$-bet ②	\$-bet ②	True	3.2
				↘	v_{P}^{+} - $v_{\$}^{-}$ = $v_{\$}^{+}$ - v_{P}^{+}	N/A	N/A	True	3.3
4	$v_{\$}^{+} > v_{\mathrm{P}}^{+}$	$v_{\mathrm{P}}^{+} > v_{\$}^{-}$	$v_{\$}^{-} > v_{\mathrm{P}}^{-}$	↗	$v_{\$}^{+}$ - v_{P}^{+} > v_{P}^{+} - $v_{\$}^{-}$ $v_{\$}^{+}$ - v_{P}^{+} > $v_{\$}^{-}$ - v_{P}^{-}		\$-bet ②	True	4.1
				→	v_{P}^{+} - $v_{\$}^{-}$ > $v_{\$}^{+}$ - v_{P}^{+} v_{P}^{+} - $v_{\$}^{-}$ > $v_{\$}^{-}$ - v_{P}^{-}	\$-bet ①	P-bet ②	True	4.2
				↘	$v_{\$}^{-}$ - v_{P}^{-} > $v_{\$}^{+}$ - v_{P}^{+} $v_{\$}^{-}$ - v_{P}^{-} > v_{P}^{+} - $v_{\$}^{-}$		\$-bet ②	False	4.3

the ①st stage when, according to the criteria of the two rules, any level of satisfaction or aspiration could be met. However, the decision maker needs further comparisons between other partworths in the ②nd stage only if a choice could not be made in the ①st stage. In Appendix C we provide logical deductions of these propositions. Summing up these theoretical assumptions, we propose the following hypothesis:

Hypothesis 4. The majority rule or the equate-to-differentiate rule predicts whether the

Table 3: Choice preferences predicted by the majority rule and the equate-to-differentiate rule, according to the two-stage payoff comparisons. (continued)

No.	①st-stage comparison: v_P^+ vs. $v_\$^+$	①st-stage comparison: v_P^+ vs. $v_\$^-$	①st-stage comparison: v_P^- vs. $v_\$^-$	Division	②nd-stage comparison (if needed)	Prediction[a]: Majority	Prediction[a]: Equate	Inequality[b]	Proposition or Conjecture
				↗	$v_\$^+ - v_P^+ > v_P^+ - v_\$^-$ $v_\$^+ - v_P^+ > v_P^- - v_\$^-$		\$-bet ②	True	5.1
5	$v_\$^+ > v_P^+$	$v_P^+ > v_\$^-$	$v_P^- > v_\$^-$	→	$v_P^+ - v_\$^- > v_\$^+ - v_P^+$ $v_P^+ - v_\$^- > v_P^- - v_\$^-$	P-bet ①	P-bet ②	True	5.2
				↘	$v_P^- - v_\$^- > v_\$^+ - v_P^+$ $v_P^- - v_\$^- > v_P^+ - v_\$^-$		P-bet ②	False	5.3
				↗	$v_P^+ - v_\$^+ > v_P^+ - v_\$^-$ $v_P^+ - v_\$^+ > v_\$^- - v_P^-$		P-bet ②	False	6.1
6	$v_P^+ > v_\$^+$	$v_P^+ > v_\$^-$	$v_\$^- > v_P^-$	→	$v_P^+ - v_\$^- > v_P^+ - v_\$^+$ $v_P^+ - v_\$^- > v_\$^- - v_P^-$	P-bet ①	P-bet ②	True	6.2
				↘	$v_\$^- - v_P^- > v_P^+ - v_\$^+$ $v_\$^- - v_P^- > v_P^+ - v_\$^-$		\$-bet ②	True	6.3
7	$v_P^+ > v_\$^+$	$v_P^+ > v_\$^-$	$v_P^- \geqslant v_\$^-$	→		P-bet ①	P-bet ①	False	7

[a] P-bet = (p_P, v_P^+; 1 - p_P, v_P^-) and \$-bet = ($p_\$$, $v_\$^+$; 1 - $p_\$$, $v_\$^-$), where v_P^+, $v_\$^+ > 0 > v_P^-$, $v_\$^-$. Key: Majority = the majority rule; Equate = the equate-to-differentiate rule; ① or ② denotes, according to the criteria of the two rules, the corresponding stage in which the decision maker could stop the payoff comparisons and make a choice. The prediction labeled "N/A" denotes the condition in which the rule is indifferent to either the P-bet or \$-bet.

[b] "True" or "False" denotes whether the inequalities in the column "②nd stage comparison (if needed)" are true or false, when the following three conditions, according to the definitions of P-bets and \$-bets, are held: $\forall$ p_P, $p_\$$, v_P^+, v_P^-, $v_\$^+$, $v_\$^- \in \mathbb{R}$, $\exists$ (1) $1 > p_P > p_\$ > 0$, (2) v_P^+, $v_\$^+ > 0 > v_P^-$, $v_\$^-$, and (3) $p_P v_P^+ + (1 - p_P) v_P^- = p_\$ v_\$^+ + (1 - p_\$) v_\$^-$—that is, the EVs of the P-bet and \$-bet are equivalent. Notice that when $p_\$ > p_P$, Propositions 2 and 7 are true. For formally logical deductions of Propositions 1.1, 1.2, 2, 3.1, 3.2, 3.3, 5.3, 6.1, and 7, see Appendix C. It is noteworthy that the proofs are not offered for Conjectures 4.1, 4.2, 5.1, 5.2, 6.3, and 6.3 due to the complexities of the absolute inequality relations of the three paired components, namely v_P^+ versus $v_\$^+$, v_P^+ versus $v_\$^-$, and v_P^- versus $v_\$^-$, in comparison with the corresponding conditions of these propositions, where at least an equality relation exists. Although there is a lack of proof for all conjectures except for Conjecture 4.3, which we found no counterexamples against it, we provided examples as proofs of their existences (see the stimulus materials in Table D.19).

P-bet or \$-bet will be chosen in a lottery (cf., Table 3).

2.3. EVDs in classic PR

The classic PR phenomenon arises in a comparison between a choice and a pricing or matching task. To the best of our knowledge, previous research on classic PR has not specifically addressed whether EVDs *between* bet pairs induce different likelihoods of PR rate. In a similar vein, Wedell and Böckenholt (1990) found that choice and pricing behaviors become more sensitive to EVDs *within* bet pairs (i.e., the EVD between the P-bet and $-bet in a given bet pair) after bet pairs are repeatedly played from 1 to 10 times. Along with multiple plays, predicted PR is also attenuated in both payoff- and EV-different conditions. Taking into account loss aversion, especially relative to the variation of possible loss payoffs when bet pairs have various EVs, we propose the following hypothesis:

Hypothesis 5. When bet pairs have higher EVs, individuals will reveal more predicted PR rates, as evidenced by choosing P-bets but overpricing $-bets.

2.4. EVDs in attraction effect PR

Context effects, also called decoy effects, indicate that people do not compare options independently of one another; instead, the phenomenon that a preference for one option over another is reversed by adding or removing further irrelevant alternatives (decoys) is called the *contextual PR* (Mellers, Ordóñez and Birnbaum, 1992). Context effects mainly consist of the attraction effect, also known as the asymmetric dominance, the compromise effect, and the similarity effect in the literature (see Ronayne and Brown, 2017 for a recent review). We illustrate the three context effects in Figure 3, which shows a map of decoy choice options located within probability × payoff space. Consider a core choice set of two options: the high-probability, low-payoff Target T, and the low-probability, high-payoff Competitor C, namely $p_T(v_T|\{T, C\})$ and $p_C(v_C|\{T, C\})$.

The *attraction* effect occurs when one of the two options is more likely to be chosen after a third alternative that is dominated by at least one of the two options is introduced (Huber, Payne and Puto, 1982). This effect can lead to the following preference inconsistency:

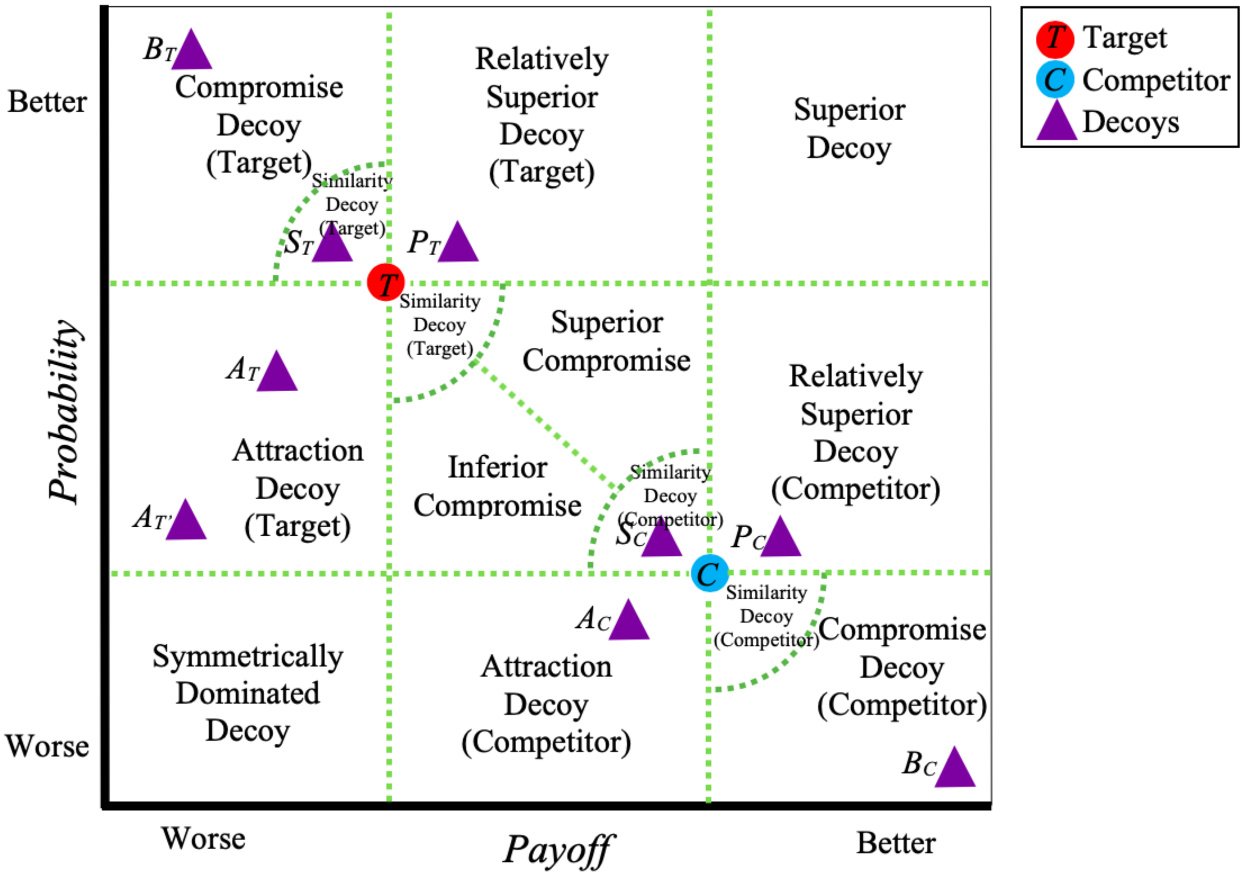


Figure 3: Decoy classifications in context effects.
Note: The example illustrates attraction decoys A_T (or $A_{T'}$) and A_C, compromise decoys B_T and B_C, and similarity decoys S_T and S_C, relative to Target T and Competitor C, respectively. The *attraction* effect is produced by the introduction of decoy A_T (A_C), which is completely dominated by Target T (Competitor C), and is thus worse on both the probability and the payoff attributes. The *phantom* effect is produced by the introduction of decoy P_T (P_C), which dominates Target T (Competitor C) on the payoff attribute, but becomes unavailable at the time of choice or valuation. The *compromise* effect is produced by the introduction of decoy B_T (B_C), which makes Target T (Competitor C) falling between decoy B_T (B_C) and Competitor C (Target T) on the probability and the payoff attributes. The *similarity* effect is produced by the introduction of decoy S_T (S_C), which closely resembles Target T (Competitor C), but is better on the probability attribute and worse on the payoff attribute.

$p_T(v_T|\{T,\ C\}) \sim p_C(v_C|\{T,\ C\})$ but $p_T(v_T|\{T,\ C,\ A_T\}) \succ p_T(v_T|\{T,\ C\})$ or $p_C(v_C|\{T,\ C,\ A_C\}) \succ p_C(v_C|\{T,\ C\})$, where the notations "$\sim$" and "$\succ$" denote the preference relations of equivalence and dominance, respectively. Thus, the presence of alternative A_T (A_C) enhances the preference for Target T (Competitor C). It is noteworthy that another class of context effects related to attraction is the *phantom* effect (see Trueblood and Pettibone, 2017 for a recent discussion). It usually happens when a third alternative is positioned so as to dominate one of the options on at least one dimension (e.g., the alternative S_T or P_T, relative to Target T, or the alternative S_C or P_C, relative to Competitor C), but is unavailable at the time of choice or valuation. This effect can lead to an increased preference for the similar, dominated option over a non-dominated one, that is, $p_T(v_T|\{T, C, P_T\}) \succ p_C(v_C|\{T, C, P_T\})$ or $p_C(v_C|\{T, C, P_C\}) \succ p_T(v_T|\{T, C, P_C\})$.

The *compromise* effect occurs when an option is more likely to be chosen after it becomes an intermediate option (Simonson, 1989). This effect can lead to the following preference inconsistency: $p_T(v_T|\{T, C\}) \sim p_C(v_C|\{T, C\})$ but $p_T(v_T|\{T, C, B_T\}) \succ p_C(v_C|\{T, C, B_T\})$ or $p_C(v_C|\{T, C, B_C\}) \succ p_T(v_T|\{T, C, B_C\})$. Thus, the presence of alternative B_T (B_C) enhances the preference for Target T (Competitor C). The *similarity* effect occurs when a third alternative that is very similar to one of the old options but neither dominates it, nor is dominated by it is introduced, such that it increases the likelihood of choosing the dissimilar option (Tversky, 1972). This effect can lead to the following PR: $p_T(v_T|\{T, C\}) \sim p_C(v_C|\{T, C\})$ but $p_C(v_C|\{T, C, S_T\}) \succ p_T(v_T|\{T, C, S_T\})$ or $p_T(v_T|\{T, C, S_C\}) \succ p_C(v_C|\{T, C, S_C\})$. Thus, the presence of alternative S_T (S_C) enhances the preference for Competitor C (Target T). All these context effects are anomalies since they violate the regularity axiom of utility theory, which holds that a preference between options should be independent of the presence of other new alternatives (Rieskamp, Busemeyer and Mellers, 2006).

In recent decades, growing evidence has been accumulated on the attraction effect. Among others, Colombo, Nicotra and Marino (2002) showed that the effect may persist when an attraction decoy is present with a low variation (e.g., A_T) rather than with a high variation (e.g., $A_{T'}$) in attributes. Frederick, Lee and Baskin (2014) indicated that the effect may be elicited more easily in numeric representations in terms of attribute payoff instead of in perceptual representations in terms of images and pie charts. Farmer (2014) observed that the effect happens in one gain-zero design but disappears in another loss-zero design. More recently, Farmer, Warren, El-Deredy and Howes (2017) provided insight into how attraction effect PR can be attenuated, though it still persists, in a gain-zero design by increasing the EVD between two bets from the level of 0% to the levels of 20%, 100%, and 300%. Even though most prior research has not attempted to vary EVDs across paired bets, the effect has still shown its robustness (e.g., Heme, 1999; Huber et al., 1982; McKenzie and Sher, 2020; Soltani, De Martino and Camerer, 2012; Trueblood, Brown, Heathcote and Busemeyer, 2013; Wedell, 1991). Similar to Hypothesis 5, we assume the same effect of EVD but in a truncated manner happened in attraction effect PR. Thus, we propose the following hypothesis:

Hypothesis 6. When target and competitor bets have higher EVD, individuals will reveal less attraction effect PR rates.

2.5. Episodic memory in PR

Now that prospects encoded in the preceding elicitation procedure (e.g., choice tasks) of a dual-task PR paradigm leave traces in episodic memory, one might expect that the aspects of prospects that might be retrieved in the subsequent procedure (e.g., price tasks) will follow the general findings in memory literature. Similar to the experimental procedure used to elicit the hindsight bias, PR can also be considered as a type of memory distortion. While pursuing novel investigations, this research proposes that PR could be explained via memory assumptions about how retrieval operates as individuals perform multiply preferential tasks, with fuzzy-trace theory being illustrative of these ideas (Brainerd et al., 2015). The theory presumes that people encode in parallel two types of memories: gist traces that store the semantic and relational content of experienced events or objects, and verbatim traces that contain the details of particular targets.

Since individuals need to distinguish between the underlying details such as words and numbers in that information, the verbatim processing requires individuals to consume more attention or working-memory capacity than that the gist processing demands (Nieznański and Obidziński, 2019). As a result, people generally prefer gist-based instead of verbatim-based processing, despite that two such representations are created. Even when verbatim details are retrievable in a judgment task, people often ignore them owing to a variety of reasons (e.g., the difficulty of accessibility, manipulability, the meaningfulness of verbatim) and make use of simplified gist information instead. Note that in PR designs using only gambling bets as stimuli, the simplest gist is categorically related to the attributes of probability and payoff, such that preferences turn on the ordinal contrast between less and more gist representations.

When we consider the role of memory in PR from the perspective of fuzzy-trace theory, we can suppose that PR happens as a result of failure to extract the verbatim representations of exact quantities (e.g., probabilities and payoffs) and the relevant gist of inputs (e.g., the bets with the low/high probability of winning the high/low payoff). In other words, retrieval of verbatim details or gist traces of bets may not be sufficient to distinguish among them, since many bets retain the same general characteristics. In particular, when people make decisions or judgments on such as bets with similar EV, the complexities of weak dominance of alternatives create confusions about which bet is preferable to another.

We postulate that the retrieval of contextual trace should be effective in restraining PR. This kind of memory trace, introduced in a recent development of fuzzy-trace theory (i.e., dual-recollection theory; Brainerd et al., 2015; Chen, Gomes and Brainerd, 2018), refers to the reinstatement of details that were accompanied by an event or episode. A decision or judgment made during the first stage of PR tasks is such a detail that accompanies the learning of bets that can be reinstated during the second stage of PR tasks (c.f., Nieznański, 2020). Given that participants may improve subsequent item recollection when they use elaborative processes of context recollection into ensemble information of bets, PR is then expected to be attenuated.

Despite the theoretical importance of memory representations in the analysis of judgmental processes, decades of research has been remarkably silent regarding the role of memory in PR phenomenon, although this is not to say that no assumptions were made with regard to memory (e.g., Aldrovandi and Heussen, 2011; Ritov, 2000; Weber and Johnson, 2006, 2009). In fact, joint analysis of PR and memory is much in its infancy. There has appeared only one relevant study so far by Belchev, Bodner and Fawcett (2018), who examined alternative choices between abstract paintings contrasting to each other on their beauties, and then later asked participants to recall their initial choices. The methodology of the study resembles a classic paradigm in memory research, wherein participants choose and encode one of two or more candidate prospects and then make memory tests about those prospects (e.g., chosen/rejected, remember/know, source). The authors identified that individuals who later misidentify their initial choices are more apt to reveal contextual PR, which suggests that choice-related memory enhancements might, in turn, ameliorate PR.

The current research extends this finding to the domain of decision making under risk, or more precisely, to consumer behavior in Experiment 3: Episodic memory in PR and to purely risk preference in Experiment 4: Episodic memory in attraction effect PR by using lottery procedures and by manipulating both choice and price paradigms. Thus, we propose the following hypothesis:

Hypothesis 7. PR will be less likely to occur when individuals could retrieve their initial choices.

All together, summarizing the causes of PR, based on half a century of research, we can say that the rate of PR is affected by the payoff scheme (e.g., gain vs. loss), payoff magnitude, elicitation procedure (e.g., choice vs. pricing), evaluation mode (joint vs. separate), irrelevant information, or episodic memory.

3. Overview of the experiments

As indicated above, in this research we investigated the possibilities that stake sizes and episodic memory may influence decision and judgment in PR in four experiments. The focus was on choice-based versus certainty-equivalent-based rankings of risky bets. Otherwise indicated, all the bets were created by the author.

In brief, Experiment 1: Magnitude effects in PR examined magnitude effects with regard to classic PR tasks. Experiment 2: Binary choices in PR investigated magnitude effects within binary choice tasks of PR on a larger scope of lottery relativity in which, under certain assumptions, people are presumed to choose some heuristic rules or, as assumed by descriptive theories of decision making, to integrate the probability and payoff attributes into subjective EVs under different prerequisites.

Experiment 3: Episodic memory in PR had several goals. First, we explored the generality of magnitude effects using a different methodology. We consistently found substantial effects in the three experiments. Second, we assessed whether the payoff-related characteristic of gambling stimuli acts as a determinant during the preference elicitation procedures of PR. Third, we tested the impact of EVD *between* bet pairs on classic PR. Fourth, we examined whether predicted and unpredicted PR stems partly from a failure to recollect bets in initial choices.

Experiment 4: Episodic memory in attraction effect PR had two goals. One was to evaluate the impact of EVD *within* bet pairs on attraction effect PR. The other was to provide extensive evidence on whether attraction effect PR also arises partly from a failure to recollect bets in initial choices. Specifically, we broadened the observations from the previous experiments to different materials being presented pictorially and with incentives influencing participants' motivation.

4. Statistical methods

In all analyses, we examined how condition-dependent expectations modulated the behavioral measure of interest (e.g., deviations from prices). We modeled all bet types simultaneously and used certain benchmark theories of risky decision making as baseline models. We used both our "novel" and other "reference" choice rules as the baseline comparison to these benchmark theories as well as analyzed individual-level data across the course of the first two sets of experiments. Conventionally, we accounted for all regressions by aggregate data and condition as a grouping variable. Then, we applied polynomial-generalized nonlinear meta-models using a built-in support for LOESS (locally estimated scatterplot smoothing) in the statistical programming language R 4.2.1 for the regression analyses (Gijbels and Prosdocimi, 2010), as determined by visual inspection, with the `ggplots` package. We also used the nonparametric statistics such as the Kruskal-Wallis, Wilcoxon rank sum, and Wilcoxon signed-rank tests (Ramachandran and Tsokos, 2021).

In order to test for the difference in the proportions of preferences within the two judgment tasks (i.e., choice and minimum selling or maximum paying price) and of the two types of PR, the binomial test for the equality of dichotomous categorical proportions was considered. The test uses the binomial distribution to decide if the outcome of an experiment using a binary variable can be attributed to a systematic effect. The test also assumes that binary variable is compared with a fixed constant (e.g., a chance level of 50%), and not with the result of any random variation. For large samples, the p value using the binomial test usually agrees with that found using the McNemar's (1969) test. For small samples ($N < 10$), the binomial test is the more reliable.

In our case, the null hypothesis is that the judgmental rates and the reversal directions in each group are the same. Each of the subjects provided from four to fifty responses in different experiments, one for each pair of bets. For statistical purposes, pooling these responses across subjects does not violate the assumptions of the binomial test, since the responses to bet pairs arising from different subjects are assumed to be independent of one another. Nevertheless, it is not assumed that different response patterns are unconditionally independent. Moreover, our analyses did not contrast a specific group with a set of other groups simultaneously; thus, the binomial test did not take the Bonferroni multiple-comparisons correction into account and yields an appropriate p value.

We eliminated noise by collapsing across trials of similar types according to the constraints imposed by repeated measures analyses of variance (ANOVA). When there were significant main effects, we further run post-hoc multiple pairwise comparisons with the Bonferroni Adjustment to determine if there were differences among the groups. The Bonferroni Adjustment was used since it is a conservative test and is more suitable when many groups are compared than other post-hoc tests. Likewise, post-hoc pairwise comparisons using Wilcoxon signed-rank test were corrected with the Benjamini-Hochberg method. All significant main effects and post-hoc effects are described, and all comparisons that are not described are not significant, unless stated otherwise. In general, we report the mean of the parameter or statistic of interest and two-sided 95% equal tail confidence intervals (CIs) around each value. We summarize the main results in the body of experimental sections and the supplementary statistical analyses in the appendixes. An alpha level of .05 was used for all statistical tests. All t-tests were two-tailed.

5. Experiment 1: Magnitude effects in PR

The present experiment aimed to test whether the magnitude of a loss ratio in a given bet pair influences choice preferences (Hypothesis 1.a and Hypothesis 1.b) and predicted and unpredicted PR (Hypothesis 2.a and Hypothesis 2.b). Prior to the main experiment, a pilot study on a small scale of bet pairs was run to preliminarily verify those hypotheses that we proposed. The main experiment was a study that elicited hypothetical responses from a different sample of subjects.

5.1. Pilot study (Lu, 2017)

5.1.1. Participants

Forty-eight undergraduate management students between 18 to 22 years old ($M = 20.5$; the female percentage was 41.2%) at Tianjin University volunteered to participate in exchange for extra course credits.

5.1.2. Design, materials, and procedure

A within-subjects design was used. Materials were three lotteries, each of which comprised a pair of two-outcome P-bet and \$-bet (see Appendix D.1). As this study was conducted in China, we showed the hypothetical payoffs in the Chinese currency Yuan (CNY) (1 CNY worth approximately €0.14 at the time of the study). Lottery 1 has relatively large differences of the losses (-10 vs. -200) and gains (110 vs. 920) between the P-bet and \$-bet. Lottery 2 has a much smaller difference of the losses (-10 vs. -15) compared with the gains (120 vs. 395) between the P-bet and \$-bet. Lottery 3 has a relatively larger absolute value of the loss (i.e., 210) than the gain (i.e., 137) in the P-bet. The EVs in the respective three pairwise bets yield the same value, except for a slight difference in the pairwise bet 3. The bets used in Lotteries 1 and 2 are taken from Li (2006). In fact, the bets in Lottery 1 are modified versions from Lichtenstein and Slovic's (1971) study, which found that the set of bets in the original version, (9/12, 1.10; 3/12, -10) for the P-bet and (3/12, 9.2; 9/12, -2) for the $-bet, would lead to the highest number of reversals. The EVs and whether those bets are P-bet or $-bet were not shown to the participants. They were firstly asked to choose between the bet pairs from the three lotteries, then to give their willingness-to-pay prices for the six bets. We also counterbalanced the three lotteries' sequences that were presented to the participants.

5.1.3. Results

We excluded one participant who did not give her willingness-to-pay on the $-bet in Lottery 2 and another one participant who did not give his choice in Lottery 3 from analyses. As in previous investigations (e.g., Bohm and Lind, 1993; Casey, 1991, 1994; Catapano et al., 2022; Chu and Chu, 1990; Gunnarsson et al., 2003; Johnson et al., 1988; Oliver and Sunstein, 2019; Seidl, 2002), we report the amount of choice, price valuation, and predicted and unpredicted PR rates in percentage (as two decimal places) and so subsequently. For the three lotteries, percentages of the participants in choice and evaluation procedures are shown in Table 4.

The pilot data demonstrate that, first, overestimating $-bet mainly accounted for PR. However, the reversal rates were not significantly different among the three lotteries, $\chi^2(4) = 5.33$, $p = .255$, and therefore did not vary much in strength when the absolute value of loss was less or more than gain in P-bet. Second, the rates of predicted and unpredicted PR were influenced by the relative magnitudes of loss in the P-bet and $-bet. When the absolute value of loss in the $-bet was significantly more than that in the P-bet (i.e., 20:1

Table 4: Percentages of choice, price valuation, and predicted and unpredicted PR: Exact two-sided binomial tests.[a]

	Choice (%)				Choice (%)				Choice (%)		
Price	P-bet	$-bet	Total	Price	P-bet	$-bet	Total	Price	P-bet	$-bet	Total
Lottery 1 (loss ratios = -20.0; gain ratio = 8.4):				Lottery 2 (loss ratios = -1.5; gain ratio = 3.3):				Lottery 3 (loss ratios = -1.1; gain ratio = 5.8):			
P-bet > $-bet	18.75	4.17^{**}	22.92	P-bet > $-bet	10.64	14.89	25.53	P-bet > $-bet	14.89	6.38	21.27
$-bet > P-bet	33.33^{**}	10.41	43.74	$-bet > P-bet	14.89	25.53	40.42	$-bet > P-bet	12.77	34.04	46.81
P-bet = $-bet	25.00	8.33	33.33	P-bet = $-bet	10.64	23.40	34.04	P-bet = $-bet	14.89	17.02	31.91
Total	77.08^{***}	22.92^{***}	$n_1 = 48$	Total	36.17	63.82	$n_2 = 47$	Total	42.55	57.44	$n_3 = 47$
p-value	< .001	.110	.001	p-value	.079	.281	1.000	p-value	.382	.050	.508
g	0.27	0.16	0.39	g	0.14	0.11	0.00	g	0.07	0.19	0.17

[a] (1) The proportionate rates of predicted and unpredicted PR are reported in these entries corresponding to "P-bet" and "$-bet > P-bet" and to "$-bet" and "P-bet > $-bet", respectively. (2) The results of the binomial tests are shown in the "p-value" and "g" entries. (3) The three binomial p-values in each of the pairwise bets show, from left to right, the test statistics of the choice, price valuation, and predicted versus unpredicted PR rates, respectively. Within the price task, we exclude the tied valuation percentages.

* $p < .05$; ** $p < .01$; *** $p < .001$.

in Lottery 1), the rate of predicted PR was significantly more than that of unpredicted PR (p = .001). On the contrary, when the losses were relatively less distinct between the P-bet and \$-bet (i.e., 3:2 and 20:21 in Lotteries 2 and 3, respectively), the rates of predicted and unpredicted PR were not significantly different ($ps > .500$).

The overall results across the three lotteries show that the preference rates within the choice task were significantly different between Lotteries 1 and 2, $\chi^2(1) = 16.20$, $p < .001$, and between Lotteries 1 and 3, $\chi^2(1) = 11.80$, $p = .001$; whereas, they were not significantly different between Lotteries 2 and 3, $\chi^2(1) = 0.40$, $p = .337$. The reason was probably due to the distinct difference of the losses between the P-bet and \$-bet in Lottery 1 (i.e., 1:20), which is much larger than that in the other two (i.e., 2:3 and 21:20 in Lotteries 2 and 3, respectively).

Thus, we preliminarily confirmed our theoretical inference: Risk preference within choice tasks of PR is significantly influenced by the change of ratio between losses. More specifically, on the one hand, when the loss in a \$-bet is significantly larger (more negative) than that in a P-bet, risk-averse preference (P-bet chosen) is significantly greater than risk-seeking preference (\$-bet chosen) within choice tasks, resulting in a significantly higher predicted PR rate than the unpredicted PR rate. On the other hand, when the losses between a P-bet and a \$-bet are not distinct, risk-averse and -seeking preferences within choice tasks are not significantly different.

5.2. Main experiment

5.2.1. Method

5.2.1.1 Participants

The participants were recruited in undergraduate psychology courses at Cardinal Stefan Wyszyński University in Warsaw. A total of 137 students between the ages of 18 and 46 ($M = 21.4$, $SD = 3.8$) volunteered to participate in the experiment and completed different tasks (outlined below). The majority was female (83.21%). The participants received no payment or course credit for participation.

5.2.1.2 Design and materials

Our design followed the standard two-step elicitation procedure in PR studies that comprises first a choice task and then a price task (e.g., Casey, 1991; Grether and Plott, 1979; Lichtenstein and Slovic, 1971). Concretely, the choice task involved choosing between the P-bet and $-bet in a given lottery, and the price task involved specifying a maximum willingness-to-pay price to each of the two binary bets in the lottery. Each lottery consisted of a P-bet and a $-bet, differing in their riskiness but not in their EV. The lotteries' payoff structure can be seen in Figure 1.

In order to avoid a possible tendency to choose a P-bet or a $-bet with the probability of gain payoff closer to 1.0, the probabilities were moderately expressed as 3 or 9 multiple of 1/12. We showed the payoffs in the Polish currency Złoty (PLN) (1 PLN worth approximately €0.24 at the time of the experiment). We elicited risk preferences using a gain-loss design. The objective was to assess the existence of PR and magnitude effects in a holistic perspective, such that both loss and gain domains are taken into consideration. Each bet was presented as the probability of winning followed by the amount of money that could be won, and then the probability of losing followed by the amount of money that could be lost. All rewards and losses were hypothetical.

Based on the pilot study, we constructed twenty-seven lotteries as materials (see Appendix D.2 for a complete list of all lottery pairs). We constrained them according to the requirements that all the P-bets have a high probability of winning a moderate amount and a low probability of losing a moderate amount, while all the $-bets have a low probability of winning a large amount and a high probability of losing a moderate to large amount. All the bets have positive EVs, ranging from 5.3 PLN to 87.5 PLN. Specifically, we manipulated their loss ratios yielding progress of increasing rates from -1.0 to -15.0. The gain ratios of these lotteries yield a range of rates between 3.3 to 65.8. Either a loss or gain ratio is computed by the loss or gain of a $-bet divided by the loss or gain of its paired P-bet, respectively (cf., Table 2). For simplicity, the levels of loss ratio are low, middle, and high.

We also manipulated each of three lotteries in a manner that yields the same loss ratio, although either their gain ratios or their EVs are impossible to be equivalent at the same time. It is important to note that among the total 137 participants, we assigned (1) 41 to complete the lotteries nos. 1 - 12 with *low* loss ratios from -1.0 to -2.5 (Set 1); (2) another 39 to complete the lotteries nos. 13 - 17 with *middle* loss ratios from -3.0 to -4.0 and the lotteries nos. 19, 20, 22, 23, 25, and 26 with *high* loss ratios from -8.0 to -15.0 (Set 2); and (3) the rest 57 to complete the lottery no. 18 with a *middle* loss ratio -4.0 and the lotteries nos. 21, 24, and 27 with *high* loss ratios from -8.0 to -15.0 (Set 3).[1] No lottery has a loss ratio ranging between -4.0 to -8.0 or larger than -15.0. Overall, the study was based on a

[1]As is aptly noticed, we did not partition these lotteries evenly, providing unbalanced numbers of four lotteries to the 57 participants, compared to the twelve and eleven lotteries to the other 41 and 39 participants, respectively. The reason is that we first collected the data from those 57 participants. Then, we increased the numbers of lotteries for the rest 41 and 39 participants in order to manipulate a wider range of loss ratios.

three-group between-subjects design. Independent variables were low versus high loss ratios, and dependent variables were risk preferences and predicted and unpredicted PR rates. We excluded the data of these lotteries with *middle* loss ratios (taken from Sets 2 and 3) from the statistical analyses with regard to hypothesis testing.

5.2.1.3 Procedure

We conducted the study in quiet classrooms. The participants received one paper-and-pencil leaflet with the full instruction and questions (the instruction and lottery examples are shown in Appendix E.1; the original text was in Polish). We asked them to complete first the choice task and then the price task, and they only completed these aforementioned lotteries which were assigned to them. The EVs, ratios, and whether these bets are P-bets or $-bets were not shown to them. We used a joint valuation elicitation procedure, such that they chose and priced the multiple lotteries simultaneously and comparatively. Within the choice task, we randomly determined the orders of lotteries to them, although we always presented first a P-bet and then a $-bet in each lottery. Within the price task, we provided the orders of the bets in conformity with their orders within the choice task. The experiment took approximately 5 to 15 minutes, and the participants answered in a self-paced manner.

5.2.2. Results

In the following, we first report the proportion of responses, followed by its data analyses within the choice and price tasks in Section 5.2.2.1 The choice task and Section 5.2.2.2 The price task, respectively. Then, we examine predicted and unpredicted PR rates in Section 5.2.2.3 Predicted and unpredicted PR. Following the literature (e.g., Ball et al., 2012; Bateman et al., 2007; Casey, 1991; Chai, 2005), we detect the asymmetry of choice, price valuation, and predicted and unpredicted PR by means of two-sided binomial exact tests. Pooled across the lotteries in the three respective sets, Table 5 shows the detailed results of the binomial tests on the percentages of choice, price valuation, and predicted and unpredicted PR. Specifically, within the price task, we calculate the binomial tests by excluding the equal valuation percentages. The reason is that according to standard theory, the strict preference, choosing Bet A over Bet B, is inconsistent with indifference, pricing Bet A and Bet B equivalently. The proportionate rates of predicted and unpredicted PR are reported in these entries corresponding to “P-bet” and “\$-bet > P-bet” and to “\$-bet” and “P-bet > \$-bet”, respectively. The results of the binomial tests are shown in the “p-value” and “g” entries. The null hypotheses are that it is equally likely for P-bets and \$-bets to be favored as well as for predicted and unpredicted PR rates. This allows us to distinguish between random and systematic risk preferences and PR types across the choice and price tasks.

5.2.2.1 The choice task

Of particular interest is whether there was a significant difference of risk preferences between these lotteries with low and high loss ratios. The binomial tests show, on the one hand, that for the lotteries with low loss ratios from -1.0 to -2.5 (taken from Set 1), the percentage that the \$-bets were chosen (M = 60.56%, SD = 7.70%) was significantly larger than the percentage that their paired P-bets were chosen (M = 39.44%, SD = 7.70%), $p < .001$, $g = 0.11$ (see Table 5). Generally speaking, when loss divergences between paired P-bets and \$-bets are no more than, in the present experiment, a -2.5:1 ratio, risk-seeking than risk-averse preference is more significant. Thus, Hypothesis 1.a was confirmed.

On the other hand, for the lotteries with high loss ratios from -8.0 to -15.0 (taken from Set 2), the percentage that the P-bets were chosen (M = 58.55%, SD = 15.67%) was significantly

Table 5: Percentages of choice, price valuation, and predicted and unpredicted PR: Exact two-sided binomial tests.[a]

Price	P-bet	$-bet	Total
	Choice (%)		
Set 1 (-2.5 $\geqslant$ loss ratios $\geqslant$ -1.0)			
P-bet > $-bet	13.42	10.77**	24.19***
$-bet > P-bet	18.70**	40.24	58.94***
P-bet = $-bet	7.32	9.55	16.87
Total	39.44***	60.56***	n_1 = 41
p-value	< .001	< .001	.002
g	0.11	0.21	0.13
Set 3 (middle loss ratio) (loss ratios = -4.0)			
P-bet > $-bet	31.58	5.26***	36.84
$-bet > P-bet	42.11***	5.26	47.37
P-bet = $-bet	12.28	3.51	15.79
Total	85.97***	14.03***	n_3 = 57
p-value	< .001	.471	< .001
g	0.36	0.06	0.39

Price	P-bet	$-bet	Total
	Choice (%)		
Set 2 (middle loss ratios) (-4.0 $\geqslant$ loss ratios $\geqslant$ -3.0)			
P-bet > $-bet	5.13	4.10***	9.23***
$-bet > P-bet	33.33***	42.05	75.38***
P-bet = $-bet	5.13	10.26	15.39
Total	43.59	56.41	n_2 = 39
p-value	.085	< .001	< .001
g	0.06	0.39	0.39
Set 3 (high loss ratio) (-15.0 $\geqslant$ loss ratios $\geqslant$ -8.0)			
P-bet > $-bet	25.73	4.68***	30.41**
$-bet > P-bet	30.99***	18.71	49.70**
P-bet = $-bet	16.38	3.51	19.89
Total	73.10***	26.90***	n_3 = 57
p-value	< .001	.006	< .001
g	0.33	0.12	0.37

Price	P-bet	$-bet	Total
	Choice (%)		
Set 2 (high loss ratios) (-15.0 $\geqslant$ loss ratios $\geqslant$ -8.0)			
P-bet > $-bet	6.41	0.86***	7.27***
$-bet > P-bet	46.58***	36.32	82.90***
P-bet = $-bet	5.56	4.27	9.83
Total	58.55*	41.45*	n_2 = 39
p-value	.011	< .001	< .001
g	0.09	0.42	0.48
Set 3 (total) (-15.0 $\geqslant$ loss ratios $\geqslant$ -4.0)			
P-bet > $-bet	27.20	4.82***	32.02**
$-bet > P-bet	33.77***	15.35	49.12**
P-bet = $-bet	15.35	3.51	18.86
Total	76.32***	23.68***	n_3 = 57
p-value	< .001	.005	< .001
g	0.36	0.11	0.38

Price	P-bet	$-bet	Total
	Choice (%)		
Set 2 (total) (-15.0 $\geqslant$ loss ratios $\geqslant$ -3.0)			
P-bet > $-bet	5.83	2.33***	8.16***
$-bet > P-bet	40.56***	38.93	79.49***
P-bet = $-bet	5.36	6.99	12.35
Total	51.75	48.25	n_2 = 39
p-value	.499	< .001	< .001
g	0.02	0.41	0.45
Sets 1, 2, and 3 (-15.0 $\geqslant$ loss ratios $\geqslant$ -1.0)			
P-bet > $-bet	13.32	6.44***	19.76***
$-bet > P-bet	29.85***	34.81	64.66***
P-bet = $-bet	8.18	7.40	15.58
Total	51.35	48.65	
p-value	.376	< .001	< .001
g	0.01	0.27	0.32

[a] (1) The three binomial p-values in each panel show, from left to right, the test statistics of the choice, price valuation, and predicted versus unpredicted PR rates, respectively. (2) According to Cohen (1988), a rule of thumb for the effect size of g can be classified as follows: 0.00 < 0.05 — Negligible; 0.10 < 0.15 — Small; 0.20 < 0.25 — Medium; 0.25 or more — Large.

* p < .05; ** p < .01; *** p < .001.

larger than the percentage that their paired \$-bets were chosen ($M = 41.45\%$, $SD = 13.73\%$), $p = .011$, $g = 0.09$. Likewise, for the lotteries with high loss ratios from -8.0 to -15.0 (taken from Set 3), the percentage that the P-bets were chosen ($M = 73.10\%$, $SD = 8.83\%$) was significantly larger than the percentage that their paired \$-bets were chosen ($M = 26.90\%$, $SD = 4.96\%$), $p < .001$, $g = 0.33$ (see Table 5). Consequently, when loss divergences between paired P-bets and \$-bets are no less than, in the present experiment, a -8.0:1 ratio, risk-averse than risk-seeking preference is more significant. Thus, Hypothesis 1.b was confirmed.

Similar to the binomial tests, Wilcoxon rank sum tests with continuity corrections show that fewer P-bets and more \$-bets were chosen among the lotteries with low loss ratios from Set 1, whereas more P-bets and fewer \$-bets were chosen among the lotteries with high loss ratios from Set 2, $z = 2.30$, $p = .021$, $\epsilon^2 = 0.54$, and among the lotteries with high loss ratios from Set 3, $z = 2.53$, $p = .011$, $\epsilon^2 = 0.65$. Besides, the same pattern was also found between the lotteries with middle loss ratios from Set 2 and the lotteries with high loss ratios from Set 3, $z = 2.10$, $p = .036$, $\epsilon^2 = 0.74$. The rest comparisons were all found not significantly different between each other (all ps $> .130$).

Summing across the overall loss ratios, the binomial tests show a monotonic risk preference between the P-bets and \$-bets for the lotteries with middle loss ratios from Set 2 ($p = .085$, $g = 0.06$), that is, the loss ratios at -3.0 and -4.0, where the participants switched their preference from risk seeking to risk averse or vice versa. Taken together, it is contended a much lower loss ratio, no more than -2.5 at the level of the data, toward a love of risk-taking preference, while a much higher loss or gain ratio, no less than -8.0 at the level of the data, toward risk-averse preference (Figure 4; cf., Figure 5 for simulations of the P-bet and \$-bet choice percentages).

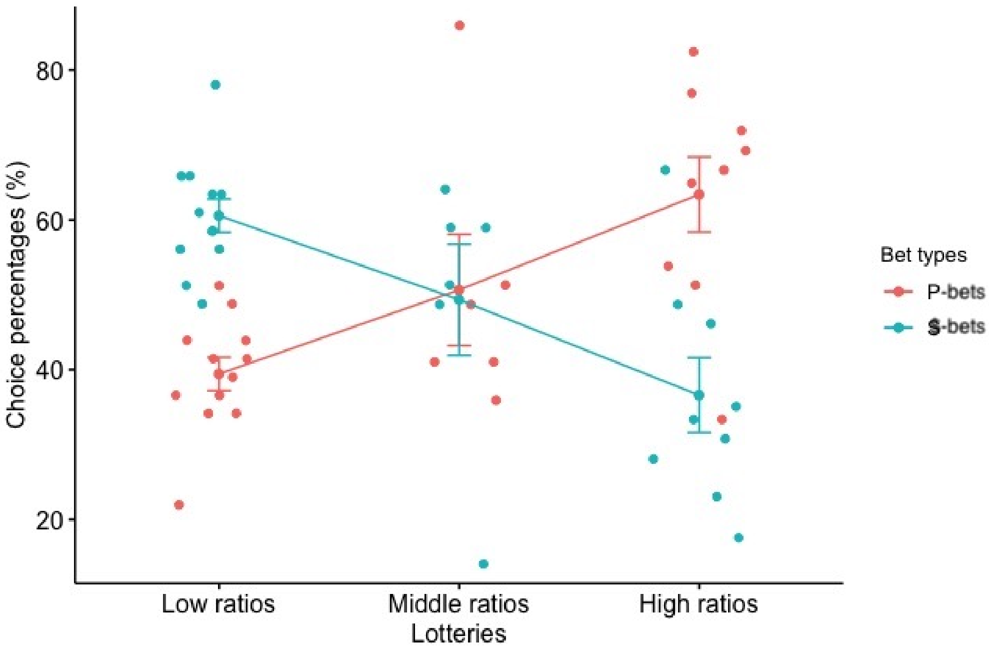


Figure 4: Percentages of choosing P-bets and $-bets by lotteries with low versus middle versus high loss ratios.
Note: Error bars are the ±1 standard error of the mean.

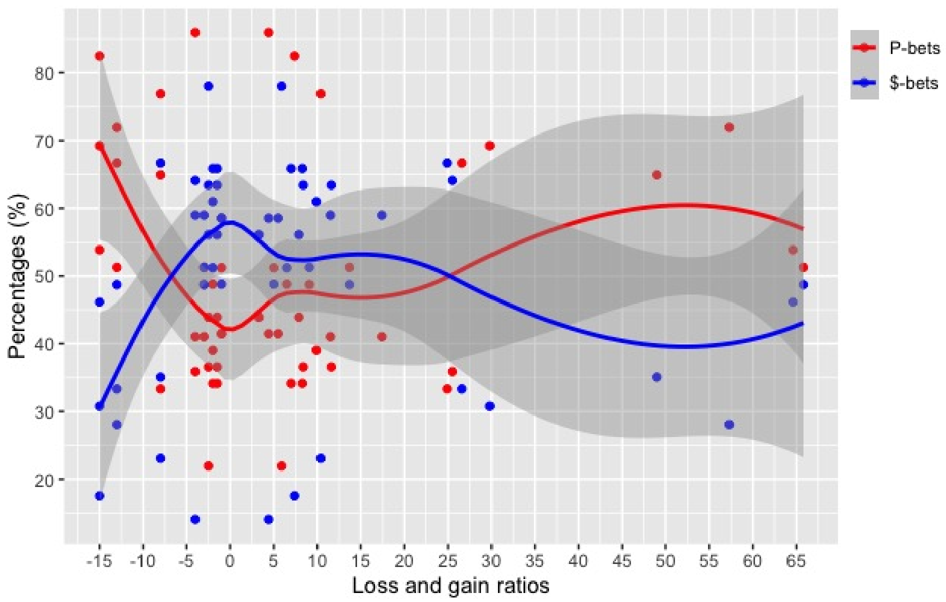


Figure 5: Simulations of the choice percentages: The separate loss and gain ratios as predictors.
Note: The shaded curves show the nonlinear (LOESS) regression functions with 95% confidence bands.

5.2.2.2 The price task

The response patterns for any pair of orderings are categorized as (1) P-bet > $-bet, (2) $-bet > P-bet, and (3) P-bet = $-bet. Strictly speaking, each subject's response patterns should be assumed to have resulted from a trinomial distribution corresponding to probabilities that fall into these three response patterns. However, we take a conservative approach to counting response patterns and ignore these ties. The results show that across all the lottery sets, with the exception of the one with the middle loss ratio (i.e., the lottery no. 18), the participants priced the \$-bets significantly higher than their paired P-bets (see Table 5). An explanation is that with the P-bet, 9/12 to win 46 PLN and 3/12 to lose 28 PLN in the lottery no. 26, for example, it is hard to image a price valuation much beyond its EV of 27.5 PLN (M = 9.85, SD = 10.61); while with its paired \$-bet, 3/12 to win 1,370 PLN and 9/12 to lose 420 PLN, it is rather common that price valuations greatly exceed the EV (M = 88.77, SD = 228.56).

Table 6 shows the mean and median price valuations and their standard derivations, as well as the results of comparisons between paired P-bets and \$-bets by Wilcoxon signed-rank tests. In general, the mean valuations were not quite close to the mean EVs for both the P-bets and \$-bets. The reason may be that although the EVs of the P-bet and \$-bet in each of our lotteries are equivalent, their gain state payoffs differ considerably by minimal 120 PLN in the lottery no. 1 and by maximal 3,940 PLN in the lottery no. 24, and the loss state payoffs also differ to a certain extent for those lotteries with high loss ratios. Among all the lottery sets, it was only observed in Set 1 that the distributions of the valuations for the \$-bets were more concentrated than those for the P-bets (i.e., $SD_{\text{P-bets}} > SD_{\text{\$-bets}}$). Taken together, these results mean that risk preferences were generally less influenced by the low versus high loss ratios.

Figure 6 depicts the separate loss or gain ratio as a predictor in nonlinear regressions with outcomes of mean-subtracted price valuations. The regression lines of the data suggest that (1) lotteries are highly skewed for these with low loss or gain ratios; (2) a risk-taking

Table 6: Price valuations (the Złoty): Wilcoxon signed-rank tests.

Descriptive statistics	Set 1		Set 2: Middle loss ratios		Set 2: High loss ratios		Set 2: Total	
	P-bets	$-bets	P-bets	$-bets	P-bets	$-bets	P-bets	$-bets
Mean EV	24.9		12.34		17.48		15.15	
Mean	16.03	20.20	8.62	34.50	8.74	80.00	8.69	59.32
Median	5	10	5	10	5	15	5	10
SD	36.56	28.18	13.64	83.09	13.11	223.88	13.34	175.87
z	-7.51		-8.82		-11.29		-14.31	
p-value	$< .001$		$< .001$		$< .001$		$< .001$	
d	0.34		0.63		0.74		0.69	
Descriptive statistics	**Set 3: Middle loss ratio**		**Set 3: High loss ratios**		**Set 3: Total**		**Sets 1, 2, and 3**	
	P-bets	$-bets	P-bets	$-bets	P-bets	$-bets	P-bets	$-bets
Mean EV	57.5		37.5		42.5		23.5	
Mean	18.02	19.97	17.36	47.01	17.52	40.25	13.58	38.78
Median	10	10	10	10	10	10	5	10
SD	18.02	22.96	20.34	140.87	19.75	123.00	27.02	123.16
z	-0.68		-3.97		-3.84		-15.36	
p-value	.500		$< .001$		$< .001$		$< .001$	
d	0.09		0.37		0.26		0.45	

behavior is prevalent for $-bets, as shown by the up-most, convexly upward curves; and (3) price valuations for $-bets rise along a concave function, with the valuatons falling off to a valley and then rising up again; moreover, loss ratios have roughly twice more impact on $-bets' mean-subtracted price valuations than do equivalently sized gain ratios—hence, there is loss aversion in accordance with the prediction of prospect theory (Kahneman and Tversky, 1979).

5.2.2.3 Predicted and unpredicted PR

Our participants replicated the inconsistency between "choice task" and "price task" well-known in the PR literature. In other words, there was a dominant asymmetry between behavior within the two tasks, which is the definition of the PR phenomenon. The results

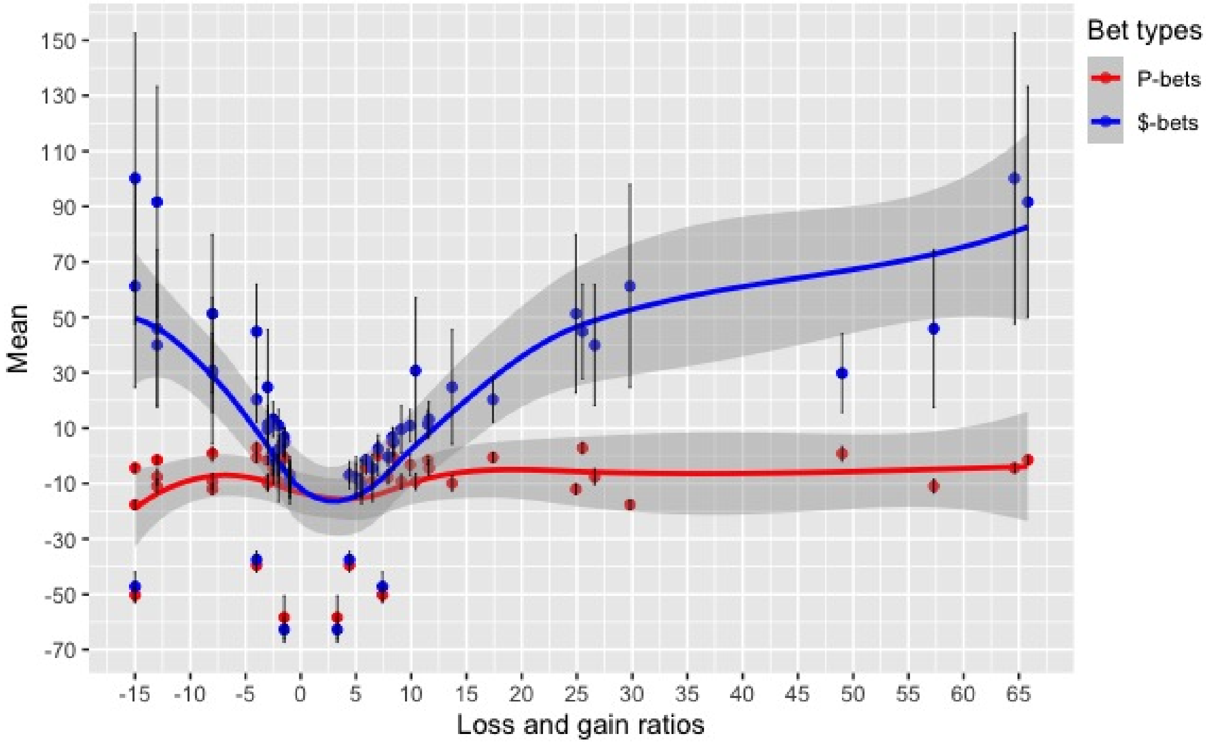


Figure 6: Simulations of the mean-subtracted willingness-to-pay price valuations: The separate loss and gain ratios as predictors.
Note: The shaded curves show the nonlinear (LOESS) regression functions with 95% confidence bands. Error bars are the ± 1 standard error of the mean.

show that, on average, predicted PR was more frequent than unpredicted PR (see Table 5). More specifically, Wilcoxon rank sum tests with continuity corrections show that, first, the predicted PR rates of the lotteries with high loss ratios from Set 2 (M = 46.58%, SD = 12.40%, Q1 = 41.67%, Q3 = 56.41%) significantly outnumbered these of the lotteries with low loss ratios from Set 1 (M = 18.70%, SD = 4.45%, Q1 = 17.07%, Q3 = 21.95%), $z = 3.35$, $p < .001$, $\epsilon^2 = 0.79$. By contrast, the unpredicted PR rates of the lotteries with low loss ratios from Set 1 (M = 10.77%, SD = 4.35, Q1 = 7.32%, Q3 = 12.81%) significantly outnumbered these of the lotteries with high loss ratios from Set 2 (M = 0.86%, SD = 1.32%, Q1 = 0.00%, Q3 = 0.00%), $z = 3.36$, $p < .001$, $\epsilon^2 = 0.79$. Surprisingly, the unpredicted PR rates of the lotteries with high loss ratios from Set 2 were so rare that they do not exceed what can be expected as a result of pure mistakes. Besides, similar patterns were also observed between the lotteries with low loss ratios from Set 1 and the lotteries with middle loss ratios from Set 2 (M = 33.33%, SD = 4.05%, Q1 = 30.77%, Q3 = 35.90%), $z_{\text{predicted}} = 3.13$, $p = .002$, $\epsilon^2 = 0.76$; $z_{\text{unpredicted}} = 2.50$, $p = .013$, $\epsilon^2 = 0.61$.

Second, the predicted PR rates of the lotteries with high loss ratios from Set 3 (M = 30.99%, SD = 1.01%, Q1 = 30.70%, Q3 = 31.58%) significantly outnumbered these of the lotteries with low loss ratios from Set 1, $z = 2.55$, $p = .011$, $\epsilon^2 = 0.66$. By contrast, the unpredicted PR rates of the lotteries with low loss ratios from Set 1 significantly outnumbered these of the lotteries with high loss ratios from Set 3 (M = 4.68%, SD = 2.68%, Q1 = 3.51%, Q3 = 6.14%), $z = 1.97$, $p = .049$, $\epsilon^2 = 0.51$. Besides, comparisons between the lotteries with low loss ratios from Set 1 and the lottery with the middle loss ratio (i.e., Lottery no. 18) yielded non-significant results (all ps $> .130$).

Taken together, these results indicate a consistent difference between predicted and unpredicted PR as a function of loss or gain ratios, suggesting that PR may persist at a lower rate in certain conditions (see Figure 7). Summing up, all these results indicate that unpredicted PR is more prevalent for the lotteries that have low loss ratios, no more than -2.5 at the level of the data. By contrast, predicted PR is more prevalent for the lotteries that have high loss ratios, no less than -8.0 at the level of the data. Therefore, Hypothesis 2.a and Hypothesis 2.b were confirmed.

Figure 8 depicts the predicted PR, unpredicted PR, non-PR (i.e., consistent preferences between choices and valuations), and equal valuation rates in terms of the separate loss and gain ratios. The nonlinear regression lines of the data indicate that (1) predicted and unpredicted PR rates are highly skewed for these lotteries with *low* loss or gain ratios, demonstrating a sizable reduction of predicted PR and a slight production of the opposite pattern of reversals; and (2) predicted PR rates rise along a concave function, with the rates

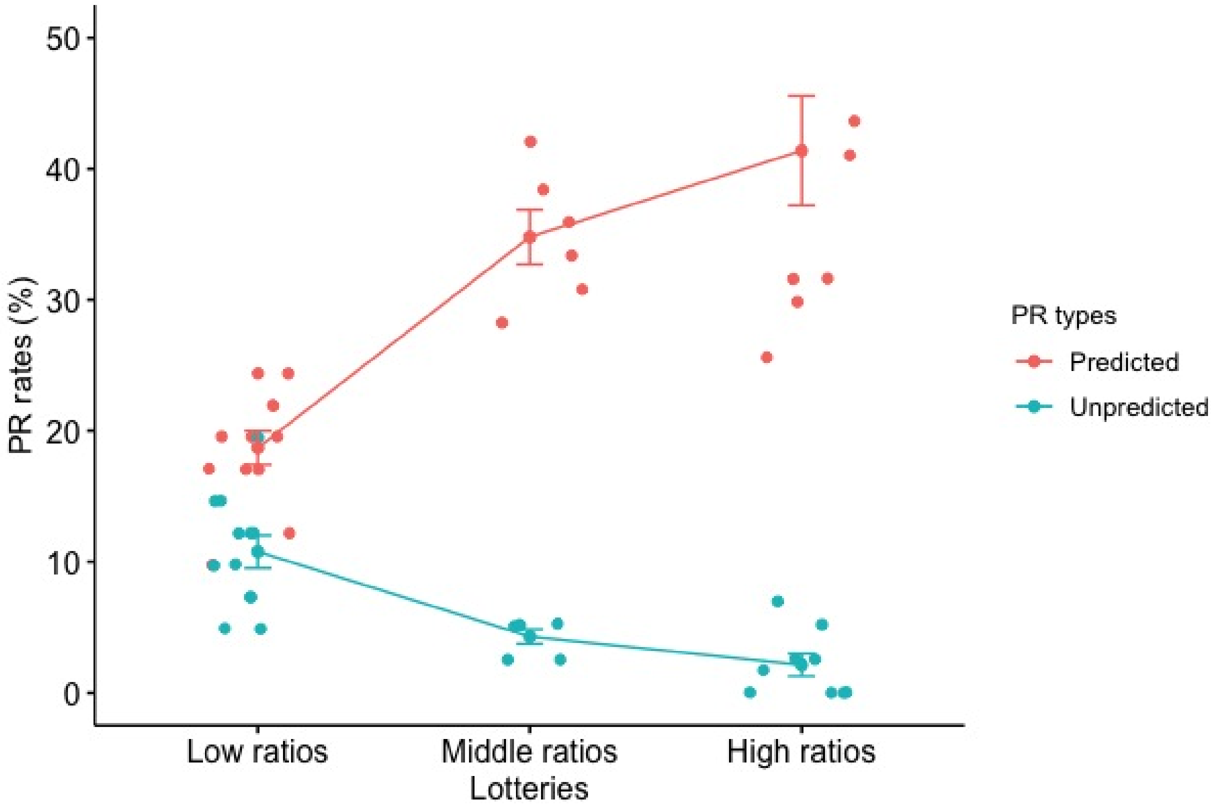


Figure 7: Predicted and unpredicted PR rates by lotteries with low versus middle versus high loss ratios. *Note*: Error bars are the ±1 standard error of the mean.

falling off to a valley, then rising up again, and next falling off again; moreover, loss ratios have a steeper slope for predicted PR rates (roughly two times larger) than do equivalently sized gain ratios—hence once again, there is robust evidence of loss aversion consistent with the prediction of prospect theory (Kahneman and Tversky, 1979).

Table 7 summarizes the individual-level results in total (the upper panel), at the low loss or gain ratios (the middle panel), and at the high loss or gain ratios (the lower panel). Overall, it indicates that many participants demonstrated predicted or unpredicted PR across some, albeit not all, lotteries. More specifically, the first numerical column in the upper panel of the table shows that 74%, 28%, and 85% of the participants in total respectively exhibited predicted PR, unpredicted PR, and predicted or unpredicted PR for at least one lottery. As can be seen, only 15% of the participants never demonstrated either predicted or unpredicted

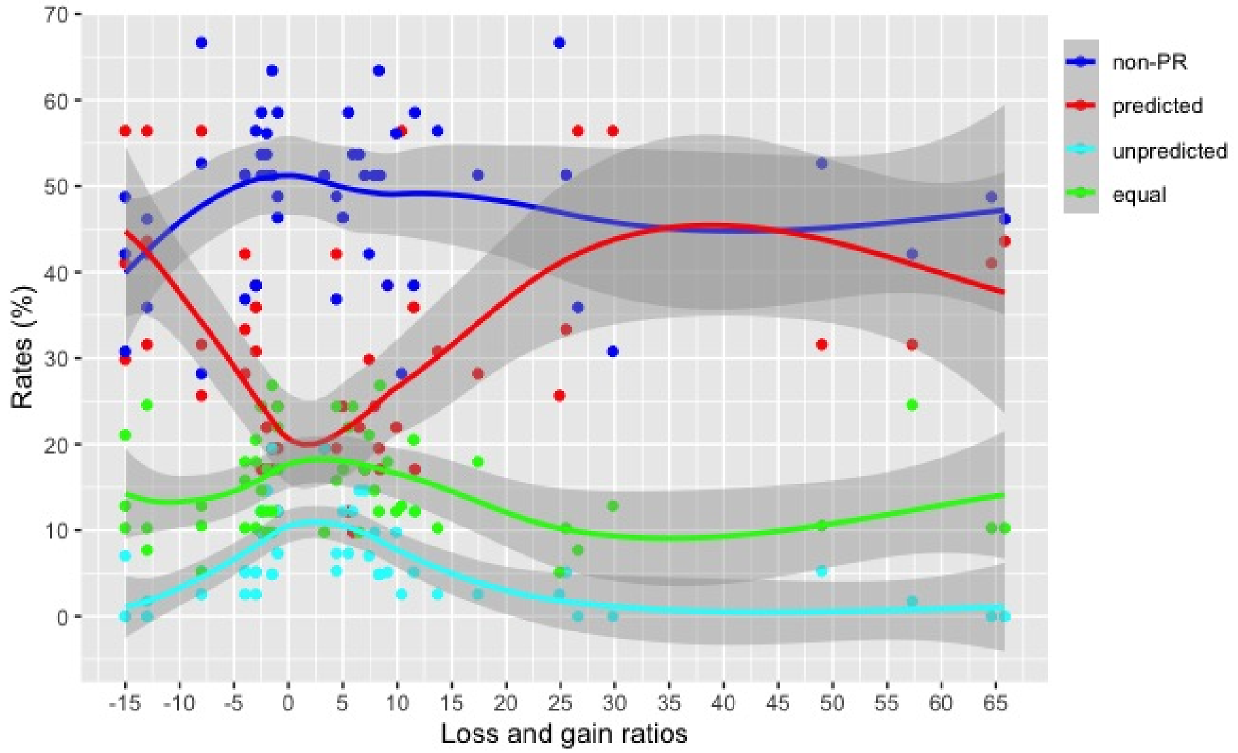


Figure 8: Simulations of scatterplots for the percentages of predicted PR, unpredicted PR, non-PR, and equal valuation: The separate loss and gain ratios as predictors.
Note: The shaded curves show the nonlinear (LOESS) regression functions with 95% confidence bands.

PR. The next twelve columns give the percentages of the participants who violated in such a way over only one lottery until over twelve lotteries. These results show that it tends to be relatively rare for a participant who violates PR consistently at every opportunity.

The first numerical column in the middle panel of the table shows that 32%, 49%, and 59% of the participants at the low loss or gain ratios respectively exhibited predicted PR, unpredicted PR, and predicted or unpredicted PR for at least one lottery. As can be seen, 41% of the participants never demonstrated either predicted or unpredicted PR. The first numerical column in the lower panel of the table shows that 97%, 21%, and 97% of the participants at the high loss or gain ratios respectively exhibited predicted PR, unpredicted PR, and predicted or unpredicted PR for at least one lottery. As can be seen, only 3% of the participants never demonstrated either predicted or unpredicted PR. Of course, those

Table 7: Individual-level incidences of violation (%).

PR types	Total	*n*-time violators 1	2	3	4	5	6	7	8	9	10	11	12
Predicted	74	15	18	13	12	3	6	5	1	0	1	2	0
Unpredicted	28	17	5	2	2	1	1	0	0	1	0	0	0
Predicted or unpredicted	85	32	37	18	14	7	9	7	2	1	1	2	0

PR types	Low loss/gain ratios	*n*-time violators 1	2	3	4	5	6	7	8	9	10	11	12
Predicted	32	10	15	17	15	2	5	5	0	0	0	0	0
Unpredicted	49	24	7	7	5	2	2	0	0	2	0	0	0
Predicted or unpredicted	59	32	24	27	22	15	12	10	2	2	0	0	0

PR types	High loss/gain ratios	*n*-time violators 1	2	3	4	5	6	7	8	9
Predicted	97	13	18	15	18	8	18	5	3	0
Unpredicted	21	18	3	0	0	0	0	0	0	0
Predicted or unpredicted	97	31	21	18	28	13	21	5	3	0

who mistook rarely might be accepted as one-off errors, attributable perhaps to a lapse in concentration. In sum, these results highlight Hypothesis 2.a and Hypothesis 2.b and suggest that PR could be attenuated when lotteries have low loss or gain ratios, no more than -2.5 at the level of the data.

5.3. Discussion

In this experiment, we categorized the loss ratios into low, middle, and high quantity extents, from -1.0 to -15.0, in a group of gamble stimuli containing twenty-seven paired bets; correspondingly, their gain ratios range from 5.0 to 49.9. We analyzed choice and price valuation data from 137 participants to test the hypotheses that loss or gain ratios of lotteries induce risk aversion or risk-seeking behavior within choice tasks as well as reveal unpredicted or predicted PR. However, we acknowledge that the experiment had defects due to unbalanced numbers of lotteries and participants per lottery set. Therefore, one should to be cautious not to overestimate the relevance of the results of this experiment.

The overall results revealed that (1) within choice tasks, low loss ratios can evoke more risk-seeking than risk-averse preference (Hypothesis 1.a), while vice versa for high loss ratios (Hypothesis 1.b); (2) overpricing of \$-bets as an account for PR is more susceptible to these paired bets with high than low loss ratios; and (3) predicted PR (i.e., P-bet chosen while \$-bet priced higher) rates can be either markedly attenuated for these paired bets with low loss ratios (Hypothesis 2.a) or increased for these paired bets with high loss ratios (Hypothesis 2.b). Based on these results, the main implications for the PR research are that risk-averse or risk-seeking preference can be elicited in decision making and that predicted PR rates can be attenuated by specific settings of loss ratios in paired P-bets and \$-bets.

5.3.1. Risk preference

The current data found a proof of ratio-dependent risk preferences within the choice task. A possible explanation is that when the loss ratio of the P-bet and \$-bet in a given lottery maintains within its threshold, presumably a -2.5:1 ratio at the level of the data, people tend to prefer the \$-bet because the gain range of the lottery is *much* wider than the loss range, that is, because the higher gain of the \$-bet is more spectacular. Alternatively, when the loss ratio becomes exceeding its threshold, presumably a -8.0:1 ratio at the level of the data, people tend to shift to prefer the P-bet because the loss range becomes exceeding enough to enable loss aversion, even though the gain range is still wider than the loss range, that is, because the lower loss of the P-bet becomes more spectacular.

Interestingly, the pattern of these results is to some extent relevant to the finding of an evolutionary-based, ratio-dependent numerosity processing system (see Gebuis, Kadosh and Gevers, 2016 or Hyde, 2011 for reviews). Several lines of evidence support the existence of the system. For instance, 6- and 10-month-old infants, species like mosquito fish, and adults can approximately discriminate the magnitudes of numerical ratio as small as 2:1, 3:2, 4:3, and 8:7, respectively (Feigenson, Dehaene and Spelke, 2004). Notice that in contrast to the choice task, there was no evidence of this pattern within the price task. Instead, in line with most of PR studies (e.g., Grether and Plott, 1979; Lichtenstein and Slovic, 1971; Loomes and Pogrebna, 2017; Tversky et al., 1990), the risk preference was largely attributable to a tendency to overbid for \$-bets but not for P-bets throughout all the loss ratios. Consequently, risk-seeking behavior was more robust than risk aversion within the price task. These results, that variations in amount to lose affected choices but not price valuations, are further evidence that the extent to which the stability of risk preference elicited under different procedures of information processing may vary dramatically due to their intrinsic differences in contextual descriptions of risk, monetary amounts, and other decision-making contents (see Kusev, Purser, Heilman, Cooke, van Schaik, Baranova, Martin and Ayton, 2017 for a review).

The evidence of ratio-dependent risk preferences is also guided by fuzzy-trace theory (Reyna, 2012). The theory posits that individuals make their decisions by relying on both gist and verbatim representations, but they prefer the former instead of the latter processing. Concretely speaking, when individuals encode, store, and retrieve information, they create qualitative "gist" representations, which operate on the essential bottom line of decision information. At the same time, individuals also create precise, quantitative "verbatim" representations. Since individuals need to distinguish between the underlying details of words and numbers in that information, the verbatim processing requires individuals to consume more attention or working-memory capacity than that the gist processing demands (Nieznański and Obidziński, 2019).

The different patterns that we observed between risk preferences within choice and price tasks may be, in some way, connected with a different level of processing imposed by each type of tasks. More specifically, choice tasks are assumed as eliciting a less affordably, albeit different, cognitive process than price tasks. The mental representations formed by this process can be contextually sensitive to the qualitative rather than to quantitative scale (Fisher and Hawkins, 1993), or more precisely, to probability or payoff attribute (Slovic and Lichtenstein, 1983; Zhou, Zhang, Li and Liang, 2018) rather than to option-based information searches within price tasks (Hinvest, Brosnan and Rogers, 2014; Zhou, Zhang, Wang, Rao, Wang, Li, ... and Liang, 2016). Importantly, it seems that individuals rely more on a gist level of processing within choice tasks because choices are general and categorical; whereas, individuals are elicited to rely on a more verbatim level of processing within price tasks because they have to declare a certain amount of money for paired bets.

As a result, the prominent "gist" representations within choice tasks, which may mainly focus on loss domains, could explain significant risk-averse preference when loss ratios between bet pairs are distinguishable over a qualitative scale. By contrast, the prominent "verbatim" representations within price tasks elicit a precision on the comparison of whole bet pairs. As Luce and Raiffa (1957, p. 25) tacitly assumed over half a century ago, violating the transitivity axiom that results in inconsistent risk preferences arises from the fact that "people have only vague likes and dislikes and they make 'mistakes' in reporting them" when manifesting their preference or indifference ordering of alternatives.

We observed that risk preferences are more congruent across choice and price tasks for these lotteries with *low* loss ratios, which is, on the one hand, consistent with some previous studies (e.g., MacDonald et al., 1992) but, on the other hand, partially against the following several prevailing theories. First, according to the attribute-dominated accounts such as prospect theory (Kahneman and Tversky, 1979) and the structure compatibility hypothesis (Selart et al., 1999), the probability attribute is more prominent than the payoff attribute in determining risk preferences within choice tasks. As a result, the majority of participants should choose P-bets instead of \$-bets, that is, risk-averse over risk-seeking preference. However, our participants exhibited a prominent risk-seeking behavior for these \$-bets with low loss ratios. Although the current study fixed the probabilities of all paired bets and, as such, could not compare the influence of the two separate attributes on the preference rates, the payoff attribute still prominently affects choice preference.

Second, our finding, that risk preferences are mixed within the choice task and are significantly risk-seeking within the price task, could not be explained by third-generation prospect theory (Schmidt, Starmer and Sugden, 2008). Contrary to different versions of prospect theory presuming a certain status quo, the framework assumes that decision weights are tied to uncertain reference points on bets. Given the asymmetry of the weighting valuation function, risk preferences shift from a more stable status within choice tasks, with a pre-experiment wealth point, to be more averse within price tasks, with a gamble endowment point. Note that since our present treatment did not manipulate the factor to specify the reference point, the observed unstable choice preferences might be due to the different stimuli which can reveal different risk preferences.

Third, our results indicate that the contingent weighting interpretation (Tversky et al., 1990) could only explain these lotteries with high loss or gain ratios. According to this theory, overestimating \$-bets is regarded as a partial reason for PR, since their payoff feature looks more salient than that of P-bets. Thus, individuals should always choose P-bets but evaluate their paired $-bets lower, which is against choice preference for these lotteries with low loss ratios. Fourth, the value encoding account of PR (Payne, 1982; Payne et al., 1992) could only underpin our finding that risk aversion is more prevalent than risk-seeking behavior when lotteries have high loss ratios. According to the account, the effect of loss aversion is extensively expected to occur within choice tasks (i.e., the so-called encoding stage) and not within price tasks. Taken together, models based on loss aversion combined with various approaches could not give accurate accounts of the data.

5.3.2. Predicted and unpredicted PR

Our results suggest that, on the one hand, predicted PR can be attenuated by shortening loss ratios to the extent to which they maintain within the low threshold, namely, -2.5 at the level of the data. By contrast, unpredicted PR can be also attenuated by widening loss ratios to the extent to which they reach the high threshold, namely, -8.0 at the level of the data. These results indicate that low variances between loss payoffs serve to dampen the tendency towards gross overpricing $-bets, and hence to reduce predicted PR. On the other hand, predicted PR can be elicited by widening loss ratios to the extent to which they reach the high thresholds, while unpredicted PR can be elicited by shortening loss ratios to the extent to which they maintain within the low thresholds.

Specifically, the observed predicted PR increased for these lotteries with high rather than low loss ratios, since the percentage of the participants choosing P-bets increased, instead of that the percentage of the participants evaluating $-bets higher than P-bets increased. This implies that the ideal lottery for observing predicted PR would have a larger ratio of loss payoffs than the high threshold presented above (facilitating choice of the P-bet). In fact, in the current experiment, the lotteries nos. 19, 23, and 26 which had the most predicted

PR (22 out of 39 reversed) had just this characteristic. Since price valuations for $-bets were closer in range to price valuations for P-bets with regard to these lotteries with low loss ratios, even fairly small fluctuations in valuation could more easily produce an increase in the occurrence of unpredicted PR, as observed.

Similarly, the ideal lottery for observing unpredicted PR would have a smaller ratio of loss payoffs than the low threshold presented above (facilitating choice of the $-bet). In fact, the lottery no. 4 which had the most unpredicted PR (8 out of 41 reversed) had just this characteristic. These findings go in line with the evidence that those subjects with the A/A genotype, who are more implusive and thus presumably more susceptible to decision biases, show stronger PR than others without this genotype when payoffs between alternatives are large (Zeng et al., 2021).

6. Experiment 2: Binary choices in PR

The present experiment aimed to gauge the accuracy of the loss-averse rule (Hypothesis 3) and of the majority rule and the equate-to-differentiate rule (Hypothesis 4) that predict choice preferences under extensive, mutually exclusive conditions. Specifically, the experiment examined, by taking into consideration the potential mediating effect of loss ratios, the explanations of the above rules and cumulative prospect theory (Tversky and Kahneman, 1992), known as an important psychological explanation of PR as well as a modification of expected utility theory, on choices between safer and riskier bets in given lotteries available across the defined propositions and conjectures.

Following Tversky and Kahneman (1992), we assume those cumulative prospect theory parameters as follows: (a) the loss aversion parameter λ in the equation (1) is equivalent to 2.25; (b) the parameters α and β in the equations (2) and (3), the powers for gain and loss payoffs, respectively, are same and equivalent to 0.88; and (c) the probability weighting parameter γ in the equation (4) is equivalent to 0.61 and 0.69 for gain and loss payoffs, respectively (cf., Section 1.4).

6.1. Method

6.1.1. Participants

One hundred thirteen Polish participants, aged between 18 and 60 years (M = 28.3, SD = 8.7, the female percentage was 60.18%), took part in the experiment. Of these, 23 participants were recruited in an undergraduate introductory course in psychology during the spring academic quarter of 2020 at Cardinal Stefan Wyszyński University in Warsaw in exchange for extra course credits. The rest 90 participants were recruited in the same year by invitation emails sent to the student body and the author's social networks, offering each person monetary reward of 50 PLN (the Polish currency Złoty; 1 PLN worth approximately €0.22 at the time of the experiment) for about 30 to 50 min of his or her time according to the feedback from the participants for this and another two independent experiments. The payments were made as online shopping cards from a Polish commercial retailer.

6.1.2. Design and materials

The experiment entailed fifty consecutive choices between two bets in given lotteries (see Appendix D.3), among which each four or six lotteries are exclusively constrained by the prerequisites of one proposition or conjecture (cf., Table 3). Each bet comprised two possible, purely hypothetical payoffs, one gain and another loss, occurring with moderate probabilities of either 75% and 25% or 60% and 40%. Moreover, each bet was presented as the probability of winning followed by the amount of money that could be won, and then the probability of losing followed by the amount of money that could be lost. We showed the possible payoffs in the Polish currency Złoty (PLN).

In addition to the lotteries in line with the prerequisites of Proposition 3.2 and Conjecture 5.1, which were conventionally employed in most of previous PR research with gain-loss designs (e.g., Cox and Grether, 1996; Grether and Plott, 1979; Lichtenstein and Slovic, 1971; Experiment 1: Magnitude effects in PR in the current study), we also extensively manipulated the other lotteries that are under the subject of the other proposition or conjecture prerequisites. Due to these constraints, there were differences in the degree to which these individual bets could also elicit different risk preferences.

Recall that when the loss ratio stays within the loss-averse threshold—that is, at the low loss ratio level, we assume that the decision maker will randomly choose either the P-bet or $-bet (cf., Section 2.2). Due to this fact, the loss-averse rule has no specific predictions regarding whether the decision maker will choose the P-bet or $-bet in this situation. Therefore, we simply presume that the percentage complying with the loss-averse rule at all levels of the low loss ratios is equivalent to that complying with the majority rule.

More concretely, for the lotteries nos. 17 - 40 complying with the prerequisites of Conjectures 4.1, 4.2, 5.1, or 5.2, we manipulated their loss ratios yielding progress of increasing rates, from -1.2, -2.0, -4.0, -6.0, -8.0 to -10.0. For the rest lotteries nos. 1 - 16 and nos. 41 - 50 complying with the prerequisites of the other propositions or conjectures, due to the nature of their conditional restrictions, it is not possible to progressively manipulate their loss ratios in the same manner as those lotteries nos. 17 - 40; otherwise, the EVs of the pairwise bets of them will not be able to yield the same value. Instead, their loss ratios are either fixed as -1.0 (Propositions 3.1 and 3.2), or different from the progressive ratios (Proposition 1.2), or partially accordant with the progressive ratios (Conjecture 6.2), or larger than the progressive ratios (Proposition 1.1 and Conjecture 6.3).

For the same reason, the EVs of the lotteries under the same propositions and conjectures are not possible to be equatable at the same time. Nevertheless, the bet pairs in each lottery always hold the same EV, ranging from 0.20 PLN to 42.00 PLN. The gains of these lotteries yield a range of rates between 1.0 to 12.2. As defined in Table 2, either a loss or gain ratio is computed by the loss or gain of a bet divided by the loss or gain of its paired bet, respectively.

Of particular interest was whether there was a significant difference of prediction by a specific one among these choice strategies for these lotteries with low loss ratios (-3.0 $\geqslant$ ratios $>$ 0) or with high loss ratios (ratios $>$ -3.0). To determine the “best” rule for each participant, a vital assumption is made that the probability of choosing in accordance with a choice strategy’s predictions is constant across proposition or conjecture conditions.

Thus, the P-bet or \$-bet favor predicted by the choice strategy is allowed only unsystematic strategy execution errors (Moshagen and Hilbig, 2011). To control for this, individual choice preferences in blocks of trials that differ in their value of the Bernoulli parameter p are compared.

6.1.3. Procedure

We conducted the experiment first in quiet classrooms for the 23 participants and then, due to COVID-19, online for the rest 90 participants, who received leaflets or questionnaires in PDF format containing all the fifty lotteries via email. We instructed them to choose one bet from each lottery, revealing their risk preference (the instruction and an example of lotteries can be found in Appendix E.2; the original text was in Polish). To control for order effects, we randomly presented the lotteries, although the orders of the two types of bets in each lottery were always first a P-bet and then a \$-bet. In order to minimize potential fatigue from a series of fifty choices, we first asked the 23 participants to complete twenty-five lotteries at the start of class. After about 1 hour, we asked them to finish the remaining twenty-five lotteries. The 23 participants answered individually at their seats and took approximately 20 minutes. The rest 90 participants answered at their own pace and sent back their completed questionnaires via email.

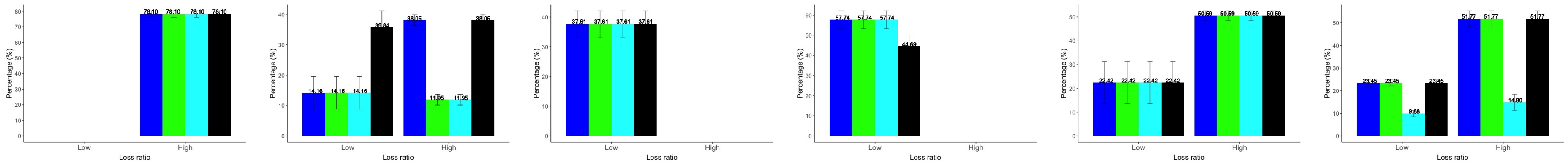
6.2. Results

We tested the two subsamples in the environments with differently calibrated measuring instruments, one an internet-based assessment and the other a paper-and-pencil administered assessment. A growing body of literature suggests the measurement equivalence of data collected via internet and face-to-face (Davidov and Depner, 2011; Shapka, Domene, Khan and Yang, 2016; Vosylis, Malinauskienė and Žukauskienė, 2012; Weigold, Weigold and

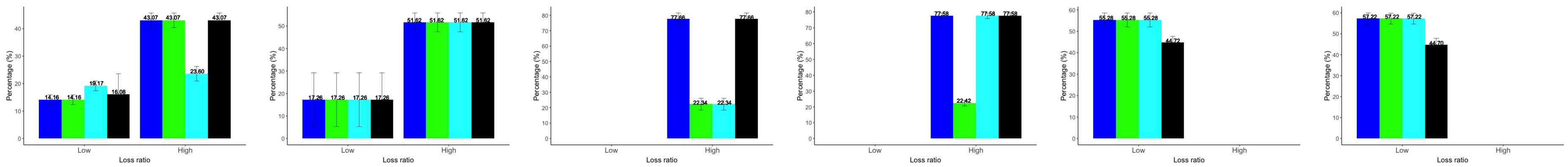
Russell, 2013). We can then assume that our study populations had the same demographic distribution and thus similar measurement error characteristics. Also, we did not take the occurrence of the COVID-19 pandemic into consideration to test whether this kind of public health emergency had any special effects on risk preference in the current research (for its possible influence on prosocial behavior, see Lu, 2022).

To ensure that an integration of all participants do not affect results, we tested all of our results below with the 23 participants as a sample and with the other 90 as another. We found no differences in conclusions. No tests statistics reported in the current research rose above or fell below significance as a result of including or excluding the data from any of the samples. Thus we report here the aggregate analyses. A frequently reported measure of the predictive performance of binary choice models is the hit rate of a model (see Franses, 2000). The hit rate is defined as the percentage of the observations that is correctly predicted by the model. The hit rate metric is complementary to first order statistics (e.g., M of the error) in determining the accuracy of a model. Table 8 shows, in 2 (low vs. high loss ratio) $\times$ 4 (the loss-averse rule vs. the majority rule vs. the equate-to-differentiate rule vs. cumulative prospect theory) contingency tables, the results of the binomial tests on the hit rates of the four choice strategies in different proposition and conjecture conditions (cf., Figure 9).

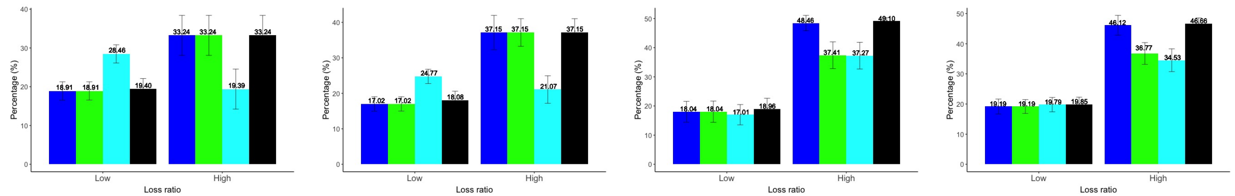
More specifically, under the Proposition 1.1, the four choice strategies yielded the same 78.10% (353 out of 452) of hit rate in the *high* loss ratio condition. Under the Proposition 1.2, the three rules yielded the same 28.32% (64 out of 226) of hit rate in the *low* loss ratio condition, whereas cumulative prospect theory yielded 71.68% (162 out of 226) of the case. By contrast, the loss-averse rule and cumulative prospect theory yielded the same 76.11% (172 out of 226), more than three times higher than the same 23.89% (54 out of 226) that the other two rules yielded, of hit rate in the *high* loss ratio condition. A similar pattern



(a) Proposition 1.1 (b) Proposition 1.2 (c) Proposition 3.1 (d) Proposition 3.2 (e) Conjecture 4.1 (f) Conjecture 4.2



(g) Conjecture 5.1 (h) Conjecture 5.2 (i) Conjecture 6.2 (j) Conjecture 6.3 (k) Proposition 3.2 (Experiment 1: Magnitude effects in PR) (l) Proposition 3.2 (Experiment 1: Magnitude effects in PR and Experiment 2: Binary choices in PR)



(m) Conjecture 5.1 (Experiment 1: Magnitude effects in PR) (n) Conjecture 5.1 (Experiment 1: Magnitude effects in PR and Experiment 2: Binary choices in PR) (o) All conditions (Experiment 2: Binary choices in PR) (p) All conditions (Experiment 1: Magnitude effects in PR and Experiment 2: Binary choices in PR)

Figure 9: Hit rates of the loss-averse rule, the majority rule, the equate-to-differentiate rule, and cumulative prospect theory: Low versus high loss ratios. *Note*: : The loss-averse rule; : The majority rule; : The equate-to-differentiate rule; : Cumulative prospect theory. Error bars are the ±1 standard error of the mean.

Table 8: Hit rates of the loss-averse rule, the majority rule, the equate-to-differentiate rule, and cumulative prospect theory: Exact two-sided binomial tests.[a]

Loss ratio	Strategy (%)			
	Averse	Majority	Equate	CPT
Proposition 1.1 (Lotteries nos. 1 - 4; Majority: $-bet; Equate: $-bet; $f_{\mathrm{H}} = 452$):				
Low	N/A	N/A	N/A	N/A
High	78.10***	78.10***	78.10***	78.10***
Total	78.10***	78.10***	78.10***	78.10***
	N/A	N/A	N/A	N/A
p-value	$< .001$	$< .001$	$< .001$	$< .001$
	$< .001$	$< .001$	$< .001$	$< .001$
	N/A	N/A	N/A	N/A
g	0.28	0.28	0.28	0.28
	0.28	0.28	0.28	0.28
Proposition 3.2 (Lotteries nos. 13 - 16; Majority: $-bet; Equate: $-bet; $f_{\mathrm{L}} = 452$):				
Low	57.74**	57.74**	57.74**	44.69*
High	N/A	N/A	N/A	N/A
Total	57.74**	57.74**	57.74**	44.69*
	.001	.001	.001	.027
p-value	N/A	N/A	N/A	N/A
	.001	.001	.001	.027
	0.8	0.8	0.8	0.5
g	N/A	N/A	N/A	N/A
	.08	.08	.08	.05
Conjecture 5.1 (Lotteries nos. 29 - 34; Majority: P-bet; Equate: $-bet; $f_{\mathrm{L}} = 226$; $f_{\mathrm{H}} = 452$):				
Low	14.16*	14.16*	19.17*	16.08
High	43.07***	43.07***	23.60***	43.07***
Total	57.23***	57.23***	42.77***	59.14***
	.028	.028	.028	.642
p-value	$< .001$	$< .001$	$< .001$	$< .001$
	$< .001$	$< .001$	$< .001$	$< .001$
	0.08	0.08	0.08	0.02
g	0.15	0.15	0.15	0.15
	0.07	0.07	0.07	0.09

Loss ratio	Strategy (%)			
	Averse	Majority	Equate	CPT
Proposition 1.2 (Lotteries nos. 5 - 8; Majority: P-bet; Equate: P-bet; $f_{\mathrm{L}} = f_{\mathrm{H}} = 226$):				
Low	14.16***	14.16***	14.16***	35.84***
High	38.05***	11.95***	11.95***	38.05***
Total	52.21	26.11***	26.11***	73.89***
	$< .001$	$< .001$	$< .001$	$< .001$
p-value	$< .001$	$< .001$	$< .001$	$< .001$
	.372	$< .001$	$< .001$	$< .001$
	0.22	0.22	0.22	0.22
g	0.26	0.26	0.26	0.26
	0.02	0.24	0.24	0.24
Conjecture 4.1 (Lotteries nos. 17 - 22; Majority: $-bet; Equate: $-bet; $f_{\mathrm{L}} = 226$; $f_{\mathrm{H}} = 452$):				
Low	22.42***	22.42***	22.42***	22.42***
High	50.59***	50.59***	50.59***	50.59***
Total	73.01***	73.01***	73.01***	73.01***
	$< .001$	$< .001$	$< .001$	$< .001$
p-value	$< .001$	$< .001$	$< .001$	$< .001$
	$< .001$	$< .001$	$< .001$	$< .001$
	0.17	0.17	0.17	0.17
g	0.20	0.20	0.20	0.20
	0.23	0.23	0.23	0.23
Conjecture 5.2 (Lotteries nos. 35 - 40; Majority: P-bet; Equate: P-bet; $f_{\mathrm{L}} = 226$; $f_{\mathrm{H}} = 452$):				
Low	17.26	17.26	17.26	17.26
High	51.62***	51.62***	51.62***	51.62***
Total	68.88***	68.88***	68.88***	68.88***
	.642	.642	.642	.642
p-value	$< .001$	$< .001$	$< .001$	$< .001$
	$< .001$	$< .001$	$< .001$	$< .001$
	0.02	0.02	0.02	0.02
g	0.27	0.27	0.27	0.27
	0.19	0.19	0.19	019

Loss ratio	Strategy (%)			
	Averse	Majority	Equate	CPT
Proposition 3.1 (Lotteries nos. 9 - 12; Majority: P-bet; Equate: P-bet; $f_{\mathrm{L}} = 452$):				
Low	37.61***	37.61***	37.61***	37.61***
High	N/A	N/A	N/A	N/A
Total	37.61***	37.61***	37.61***	37.61***
	$< .001$	$< .001$	$< .001$	$< .001$
p-value	N/A	N/A	N/A	N/A
	$< .001$	$< .001$	$< .001$	$< .001$
	0.12	0.12	0.12	0.12
g	N/A	N/A	N/A	N/A
	0.12	0.12	0.12	0.12
Conjecture 4.2 (Lotteries nos. 23 - 28; Majority: $-bet; Equate: P-bet; $f_{\mathrm{L}} = 226$; $f_{\mathrm{H}} = 452$):				
Low	23.45***	23.45***	9.88***	23.45***
High	51.77***	51.77***	14.90***	51.77***
Total	75.22***	75.22***	24.78***	75.22***
	$< .001$	$< .001$	$< .001$	$< .001$
p-value	$< .001$	$< .001$	$< .001$	$< .001$
	$< .001$	$< .001$	$< .001$	$< .001$
	0.20	0.20	0.20	0.20
g	0.28	0.28	0.28	0.28
	0.25	0.25	0.25	0.25
Conjecture 6.2 (Lotteries nos. 41 - 44; Majority: P-bet; Equate: P-bet; $f_{\mathrm{H}} = 452$):				
Low	N/A	N/A	N/A	N/A
High	77.66***	22.34***	22.34***	77.66***
Total	77.66***	22.34***	22.34***	77.66***
	N/A	N/A	N/A	N/A
p-value	$< .001$	$< .001$	$< .001$	$< .001$
	$< .001$	$< .001$	$< .001$	$< .001$
	N/A	N/A	N/A	N/A
g	0.28	0.28	0.28	0.28
	0.28	0.28	0.28	0.28

Table 8: Hit rates of the loss-averse rule, the majority rule, the equate-to-differentiate rule, and cumulative prospect theory: Exact two-sided binomial tests.[a] (continued)

Conjecture 6.3 (Lotteries nos. 45 - 50; (Majority: P-bet; Equate: \$-bet; $f_{\mathrm{H}} = 678$):

Loss ratio	Strategy (%) Averse	Majority	Equate	CPT
Low	N/A	N/A	N/A	N/A
High	77.58^{***}	22.42^{***}	77.58^{***}	77.58^{***}
Total	77.58^{***}	22.42^{***}	77.58^{***}	77.58^{***}
	N/A	N/A	N/A	N/A
p-value	< .001	< .001	< .001	< .001
	< .001	< .001	< .001	< .001
	N/A	N/A	N/A	N/A
g	0.28	0.28	0.28	0.28
	0.28	0.28	0.28	0.28

Proposition 3.2 (Lotteries nos. 1 - 3 in Experiment 1: Magnitude effects in PR; Majority: \$-bet; Equate: \$-bet; $f_{\mathrm{L}} = 123$):

Loss ratio	Strategy (%) Averse	Majority	Equate	CPT
Low	55.28	55.28	55.28	44.72
High	N/A	N/A	N/A	N/A
Total	55.28	55.28	55.28	44.72
	.279	.279	.279	.279
p-value	N/A	N/A	N/A	N/A
	.279	.279	.279	.279
	0.05	0.05	0.05	0.05
g	N/A	N/A	N/A	N/A
	0.05	0.05	0.05	0.05

Proposition 3.2 (Lotteries nos. 1 - 3 in Experiment 1: Magnitude effects in PR and Lotteries nos. 13 - 16 in Experiment 2: Binary choices in PR; Majority: \$-bet; Equate: \$-bet; $f_{\mathrm{L}} = 575$):

Loss ratio	Strategy (%) Averse	Majority	Equate	CPT
Low	57.22^{***}	57.22^{***}	57.22^{***}	44.70^{*}
High	N/A	N/A	N/A	N/A
Total	57.22^{***}	57.22^{***}	57.22^{***}	44.70^{*}
	< .001	< .001	< .001	.012
p-value	N/A	N/A	N/A	N/A
	< .001	< .001	< .001	.012
	0.07	0.07	0.07	0.05
g	N/A	N/A	N/A	N/A
	0.07	0.07	0.07	0.05

Conjecture 5.1 (Lotteries nos. 4 - 27 in Experiment 1: Magnitude effects in PR; Majority: P-bet; Equate: \$-bets; $f_{\mathrm{L}} = 486$; $f_{\mathrm{H}} = 540$):

Loss ratio	Strategy (%) Averse	Majority	Equate	CPT
Low	18.91^{***}	18.91^{***}	28.46^{***}	19.40^{***}
High	33.24^{***}	33.24^{***}	19.39^{***}	33.24^{***}
Total	52.15	52.15	47.85	52.63
	< .001	< .001	< .001	< .001
p-value	< .001	< .001	< .001	< .001
	.179	.179	.179	.098
	0.10	0.10	0.10	0.09
g	0.13	0.13	0.13	0.13
	0.02	0.02	0.02	0.03

Conjecture 5.1 (Lotteries nos. 4 - 27 in Experiment 1: Magnitude effects in PR and Lotteries nos. 29 - 34 in Experiment 2: Binary choices in PR; Majority: P-bet; Equate: \$-bet; $f_{\mathrm{L}} = 712$; $f_{\mathrm{H}} = 992$):

Loss ratio	Strategy (%) Averse	Majority	Equate	CPT
Low	17.02^{***}	17.02^{***}	24.77^{***}	18.08^{***}
High	37.15^{***}	37.15^{***}	21.07^{***}	37.15^{***}
Total	54.17^{***}	54.17^{***}	45.84^{***}	55.23^{***}
	< .001	< .001	< .001	< .001
p-value	< .001	< .001	< .001	< .001
	< .001	< .001	< .001	< .001
	0.09	0.09	0.09	0.07
g	0.14	0.14	0.14	0.14
	0.04	0.04	0.04	0.05

All conditions (Lotteries nos. 1 - 50 in Experiment 2: Binary choices in PR; $f_{\mathrm{L}} = 2034$; $f_{\mathrm{H}} = 3616$):

Loss ratio	Strategy (%) Averse	Majority	Equate	CPT
Low	18.04	18.04	17.01^{*}	18.96^{*}
High	48.46^{***}	37.41^{***}	37.27^{***}	49.10^{***}
Total	66.50^{***}	55.45^{***}	54.28^{***}	68.05^{***}
	.947	.947	.014	.018
p-value	< .001	< .001	< .001	< .001
	< .001	< .001	< .001	< .001
	0.00	0.00	0.03	0.03
g	0.26	0.09	0.08	0.27
	0.17	0.06	0.04	0.18

Table 8: Hit rates of the loss-averse rule, the majority rule, the equate-to-differentiate rule, and cumulative prospect theory: Exact two-sided binomial tests.[a] (continued)

	Strategy (%)			
Loss ratio	Averse	Majority	Equate	CPT
	All conditions			
	(Lotteries nos. 1 - 27 in Experiment 1: Magnitude effects in PR and Lotteries nos. 1 - 50 in Experiment 2: Binary choices in PR;			
	f_{L} = 2520; f_{H} = 4156):			
Low	19.19	19.19	19.79*	19.85*
High	46.12***	36.77***	34.53***	46.66***
Total	65.31***	55.96***	54.32***	66.51***
	.414	.414	.016	.010
p-value	< .001	< .001	< .001	< .001
	< .001	< .001	< .001	< .001
	0.01	0.01	0.02	0.03
g	0.24	0.09	0.06	0.25
	0.15	0.06	0.04	0.17

[a] (1) Key: Averse = the loss-averse rule; Majority = the majority rule; Equate = the equate-to-differentiate rule; CPT = cumulative prospect theory. (2) The low and high loss ratios are categorized according to whether they are no more or less than 3.0, respectively. (3) The predictions of the majority rule and the equate-to-differentiate rule under the conditions of the propositions and conjectures are in parentheses (cf., Table 3). (4) The symbols f_{L} and f_{H} denote frequency responses (observation numbers) with regard to the low loss ratios (-3.0 $\geqslant$ ratios > 0) and the high loss ratios (ratios > -3.0), respectively. (5) The three two-sided binomial p-values and the effect sizes of g show, from up to down, the test statistics of choices with regard to the low, high, and total loss ratios, respectively. (6) The effect size of g can be classified as follows: 0.00 < 0.05 — Negligible; 0.10 < 0.15 — Small; 0.20 < 0.25 — Medium; 0.25 or more — Large. N/A = not applicable.

* $p < .05$; ** $p < .01$; *** $p < .001$.

was also observed under the Conjecture 6.2.

Under the Proposition 3.1, the four choice strategies yielded the same 37.61% (170 out of 452) of hit rate in the *low* loss ratio condition. Under the Proposition 3.2, the three rules yielded the same 57.74% (261 out of 452) of hit rate in the *low* loss ratio condition, whereas cumulative prospect theory yielded 44.69% (202 out of 452) of the case. A similar pattern was also observed under the Proposition 3.2 (Experiment 1: Magnitude effects in PR). Under the Conjecture 4.1, the four choice strategies yielded the same 67.26% (152 out of 226) and 75.89% (343 out of 452) of hit rate in the *low* and *high* loss ratio conditions, respectively. A similar pattern was also observed under the Conjecture 5.2.

Under the Conjecture 4.2, which includes most of the previous PR research with gain-loss designs, there were 70.35% (159 out of 226), 70.35% (159 out of 226), 29.65% (67 out of 226), and 70.35% (159 out of 226) of the choices in the *low* loss ratio condition complying with the predictions of the loss-averse rule, the majority rule, the equate-to-differentiate rule, and cumulative prospect theory, respectively. These divergences were significantly different compared with those of 77.66% (351 out of 452), 77.66% (351 out of 452), 22.35% (101 out of 452), and 77.66% (351 out of 452) of the choices in the *high* loss ratio condition, $\chi^2(1) = 4.31$, $p = .038$, $d = 0.16$. Following Cohen's guideline ($d = 0.20$, 0.50, and 0.80 for small, medium, and large effects, respectively; cf., Cohen, 1992), the difference between the means of the two compared conditions for these choices was a small effect. A similar pattern was also observed under such as the Conjecture 5.1, $\chi^2(1) = 30.13$, $p < .001$, $d = 0.36$, and the Conjecture 5.1 (Experiment 1: Magnitude effects in PR), $\chi^2(1) = 55.32$, $p < .001$, $d = 0.48$.

Under the Conjecture 6.3, the loss-averse rule, the equate-to-differentiate rule, and cumulative prospect theory yielded the same 77.58% (526 out of 678), more than three times higher than 22.42% (152 out of 678) that the majority rule yielded, of hit rate in the *high* loss ratio condition. Pooled all the low and high loss ratio conditions and the propositions and conjectures together, the loss-averse rule, the majority rule, the equate-to-differentiate rule, and cumulative prospect theory correctly predicted the observed choice in 66.50% (3757 out of 5650), 53.36% (3015 out of 5650), 52.20% (2949 out of 5650), and 68.05% (3845 out of 5650) of the cases, respectively.

Taken together, the overall results indicate that when decision makers choose between bet pairs whose loss ratios are no more than -3.0 at the level of the data, their judgments show no significant differences among the four choice strategies. The choices made by the loss-averse rule, the majority rule, the equate-to-differentiate rule, and cumulative prospect theory correctly predicted the observed choice in 50.10% (1019 out of 2034), 50.10% (1019 out of 2034), 47.25% (961 out of 2034), and 52.66% (1071 out of 2034) of the cases, respectively. Conversely, when decision makers choose between bet pairs whose loss ratio are no less than -3.0, their judgments are more consistent with cumulative prospect theory and the loss-averse rule of decision than with the majority rule or the equate-to-differentiate rule. The choices made by the four identified strategies correctly predicted the observed choice in 76.72% (2774 out of 3616), 75.72% (2738 out of 3616), 55.20% (1996 out of 3616), and 54.98% (1988 out of 3616) of the cases, respectively.

The patterns of hit rate were significantly divergent between the *low* and *high* loss ratio conditions, $\chi^2(1) = 23.93$, $p < .001$, $d = 0.13$. A similar pattern was also observed when the data of Experiment 1: Magnitude effects in PR and Experiment 2: Binary choices in PR were combined. These results support an effect of stake sensitivity on *high* loss ratios, which may serve as an alarm index of loss avoidance. Thus, when loss ratios of lotteries are relatively higher than -3.0 at the level of the data, individuals may be more likely to choose, among others, the loss-averse rule as a behavioral decision heuristic at hand underlying choice preference judgments. Therefore, Hypothesis 3 was confirmed.

In addition, there was sufficient variability within the characteristics of loss and gain payoffs of the bets to permit analysis of their relationship to the participants' risk preferences. This analysis indicates that the difference between the amount to lose in the P-bet and the amount to lose in the $-bet correlated .78 across the fifty lotteries with the number of the participants who chose the bet with the smaller absolute value of loss payoff. More precisely, first, under the Propositions 1.1 and 1.2 and Conjectures 4.1, 4.2, 6.2, and 6.3, where the amount to lose in the $-bet is smaller than the amount to lose in the P-bet, the participants chose the $-bet 76% (2569 out of 3390) of the time. Specifically, when the loss ratio is no less than -3.0, the $-bet was chosen 77% (2096 out of 2712) of the time. Second, under the Conjectures 5.1 and 5.2, where the reverse is true, the P-bet was chosen 63% (855 out of 1356) of the time. Specifically, when the loss ratio is no less than -3.0, the P-bet was chosen 71% (642 out of 904) of the time. Third, under the Propositions 3.1 and 3.2, where the amounts to lose in both the P-bet and $-bet are equivalent, the participants chose the $-bet 60% (543 out of 904) of the time.

By contrast, the variations in amount to win had rather less effect on the choices. More precisely, first, under the Propositions 3.1 and 3.2 and Conjectures 4.1, 4.2, 5.1, and 5.2, where the amount to win in the $-bet is larger than the amount to win in the P-bet, the participants chose the $-bet 67% (2403 out of 3616) of the time. Second, under the Conjectures 6.2 and 6.3, where the reverse was true, the P-bet was only chosen 22% (253 out of 1130) of the time. Third, under the Propositions 1.1 and 1.2, where the amounts to win in both the P-bet and $-bet are equivalent, the participants chose the safer $-bet 76% (687 out of 904) of the time. By contrast, under the Propositions 3.1 and 3.2, where the amounts to lose in both the P-bet and $-bet are equivalent, the participants chose the riskier $-bet only 60%

(543 out of 904) of the time. Thus, a comparison of the Propositions 1.1 and 1.2 conditions, where the mean difference of loss payoffs is 23.50 PLN ($SD = 20.26$), with the Propositions 3.1 and 3.2 conditions, where the mean difference of gain payoffs is 26.63 PLN ($SD = 20.78$), also suggests that risk aversion is engaged more than risk-seeking behavior. These results, that variations in amount to lose rather than to win affected choices, are further evidence that the same amount to lose looms larger than the same amount to win in choosing.

Further analyses regarding loss aversion appear in Appendix F, which shows a prevailing preference of loss averse choice that was indifferent to distributions of losses and gains.

6.3. Discussion

Our methods for gauging the accuracy of a model with reasonable competitors included could tell whether some heuristic and more complex strategies are used by some individuals or not. This allows for internally valid conclusions concerning the usage of a heuristic rule or a more complex strategy such as cumulative prospect theory (Jekel and Glöckner, 2018). Nevertheless, the current methodology is not specifically designed to test the underlying processes of these rules and cumulative prospect theory critically, but rather to provide relative insights into whether one choice strategy could account for the data better than another.

Importantly, the findings from the current hit rate comparison that specify one choice strategy providing a better account of the data over another might be caused by the simulated choice sets that were typically designed for PR, in which the EVs of the P-bet and $-bet are equivalent. Thus, the predictive accuracy of one choice strategy might not be the same case for other decision tasks. Moreover, those findings should not be over-interpreted as evidence that decision makers truly use the specific choice strategy. Instead, even a model that accounts well for the data does not necessarily represent the true underlying process, since all models are only necessary abstractions (see Roberts and Pashler, 2000 for a discussion).

Attempts to model preferential choices under risk and uncertainty have traditionally led to increasingly complex models which attempt to consider factors like overweight low-probability events, expected utility relative to a reference point, and loss aversion (e.g., cumulative prospect theory). By contrast, heuristic decision strategies, such as the loss-averse rule, have abandoned the attempt to duplicate a complex reality for much simpler modeling approaches. It concludes by suggesting that certain heuristic rules can also play a critical role that complex models have in attempts to forecast preferential choices.

7. Experiment 3: Episodic memory in PR

The goals of the present experiment were to test whether (1) EVDs between bet pairs affect PR (Hypothesis 5); and (2) correct retrievals of initial choice judgments ameliorate PR (Hypothesis 7). To achieve the goals, we varied the EVs of the non-decoy lotteries to test for the effect of this parameter on the frequency of PR. What is novel is that we included a memory test in the last phase of the experiment so that subjects' accuracy of recalling the choices that they had made can be measured to test for an association between a subject's rate of accuracy in the memory test and their rate of PR. As a memory cue, each lottery choice set was attached to a product picture, such as a couch or a coffee machine.

7.1. Participants

Sixty-four introductory psychology students, aged between 20 and 47 years ($M = 20.9$, $SD = 3.6$; the female percentage was 79.69%), from Cardinal Stefan Wyszyński University in Warsaw participated in the experiment in exchange for extra course credits.

7.2. Materials

The materials consisted of 2 paired gambling options as fillers (Nos. 1 - 2), another 22 paired gambling options as targets (Nos. 3 - 24, the upper two bets), remaining 22 paired gambling options as distractors (Nos. 3 - 24, the lower two bets), as well as their corresponding 24 colored images of commercial products from local markets and their manufacturer's suggested retail prices (MSRPs) (see Table D.20 in Appendix D.4). Fillers (or buffers) were items routinely used in memory research to neutralize the effects of primacy and recency. Targets were items that had been presented at the first (study) phase of the experiment, and distractors were items that were not presented at study.

More precisely, these 22 paired distractor options, which differed from their paired target options (one pair of distractors per each paired target options) only in their probability dimensions, consisted of 22 distractors correlating with the “P-bet” options and the remaining 22 distractors correlating with the “\$-bet” options. Among these stimuli, each of the 24 images co-occurred with only one pair of filler or target options, and each of the 22 paired distractor options co-occurred with only one pair of target options.

The MSRPs per single product ranged within the following four scopes: (1) 3.0 to 4.0 PLN, (2) 30.0 to 48.0 PLN, (3) 370.0 to 600.0 PLN, and (4) 1250.0 to 1600.0 PLN, which yielded the EVs of the target options ranging from (1) 4.4 to 8.4 PLN, (2) 24.0 to 84.0 PLN, (3) 467.5 to 1200.0 PLN, and (4) 1550.0 to 2800.0 PLN, respectively.[2] Although these target options varied their EVs in different extents among each other pairs, they had always the same EV in each pair. The manipulations of MSRPs and EVs allowed us to test Hypothesis 5.

7.3. Design

We designed a source memory paradigm in which the context was defined by the decision to accept or reject an option. The experiment comprised three blocks. The first block consisted of 24 choice trials including both the 2 paired filler options and 22 paired target options. The participants were instructed to make time-limited choices, for each gamble pair, between (1) a “P-bet” option, a high probability p_{P} of winning one or several pieces of a product and a probability 1 - p_{P} of losing one or several pieces of the same product, where p_{P} was equal to 70%, 75%, 80%, or 85%; and (2) a “\$-bet” option, a low to moderate probability $p_{\$}$ of winning one or several pieces of the same product and a probability 1 - $p_{\$}$ of losing one or several pieces of the same product, where $p_{\$}$ was correspondingly equal to

[2]We also manipulated another two paired gambling options as targets (MSRPs = 3.3 and 390 PLN; EVs = 7.3 and 780.0 PLN) aimed at yielding the same number of gambling options in each EV condition, but due to programming errors these data could not be included.

30%, 25%, 20%, or 15%. An enforced assessment duration allowed us to control the amount of time that the participants put into each trial.

We also indicated the MSRP of each product beside its image and constructed the EVs of each paired target options equivalent to the same value. Specifically, we manipulated the loss ratios of the 22 paired target options, such that they yielded progress of increasing rates from -1.0 to -10.0 (we add a minus sign for each loss ratio), as calculated by dividing the losses of "$-bet" options by the losses of their respective "P-bet" options. Correspondingly, the gain ratios of them yielded, albeit not progressively, a range of rates between 3.0 and 50.0. Take No. 3 the "P-bet" option (70%, 2; 30%, -1) and its paired "$-bet" option (30%, 6; 70%, -1) that were attached to a set of Italian blanket and bed as a memory cue for example—the MSRP per single set is 425.0 PLN, thus yielding (1) the EVs of both the "P-bet" and "$-bet" options equivalent to the same 467.5 PLN, (2) the loss ratio of them equivalent to -1.0, and (3) the gain ratio of them equivalent to 3.0. We implemented these progressive loss and gain ratios in order to re-examine the generality of Hypothesis 1.a, Hypothesis 1.b, Hypothesis 2.a, and Hypothesis 2.b.

The second block consisted of a series of 48 price trials including both the 2 paired filler options and the 22 paired target options. The participants were asked to make self-paced assessments in a separate evaluation mode (i.e., the participants could only view one option at a time), specifying their minimum willingness-to-accept prices for these "P-bet" and "$-bet" options.

The third block consisted of 44 memory probes taken from the 22 target pairs and their corresponding 22 distractor pairs (two probes per product). Among these probes, 22 probes consisted of 11 target "P-bet" options and 11 target "$-bet" options (one target option per product), and the remaining 22 probes consisted of 11 distractor "P-bet" options and

11 distractor "$-bet" options (one distractor option per product). Following the conjoint recognition paradigm (e.g., Brainerd et al., 2015), each probe was paired with one of the following 3 episodic memory questions that the participants were requested to respond: (a) Did you choose the option? (*C?*; in Polish, Czy wybrałeś ten zakład?); (b) Did you reject the option? (*R?*; in Polish, Czy odrzuciłeś ten zakład?); and (c) Did you choose or reject the option? (*C or R?*; in Polish, Czy wybrałeś lub odrzuciłeś ten zakład?), where the memory probes (a) and (b) concern source (context) memory for specific choices, whereas the probe (c) is a recognition memory question in which participants have to distinguish targets from distractors. Each of the 3 episodic memory questions comprised 12 or 16 probes (half probes were target options, and another half distractor options), and none of the individual option that appeared in one memory probe appeared in another. The participants were asked to make self-paced responses. We manipulated these distractor options and questions in order to examine Hypothesis 7, such that the observed responses reflect context discrimination and target recognition processes contributing to memory performance.

7.4. Apparatus and procedure

During the experiment, all the materials and instructions were presented on a computer screen, and the participants' responses were recorded by E-Prime 2.0. Following the conventional PR paradigm and the standard memory research, we first run the choice task, then the price task, and finally the memory test (see Figure 10). Within the choice and price tasks, every trial always began with a slide displaying a fixation point "+" presented at a 0.5-second rate in the middle of the screen. The background color of the screen was white.

More specifically, in the first "choice task" block, a "P-bet" option and its paired "$-bet" option were presented side by side, centered on the screen, printed with the two options in

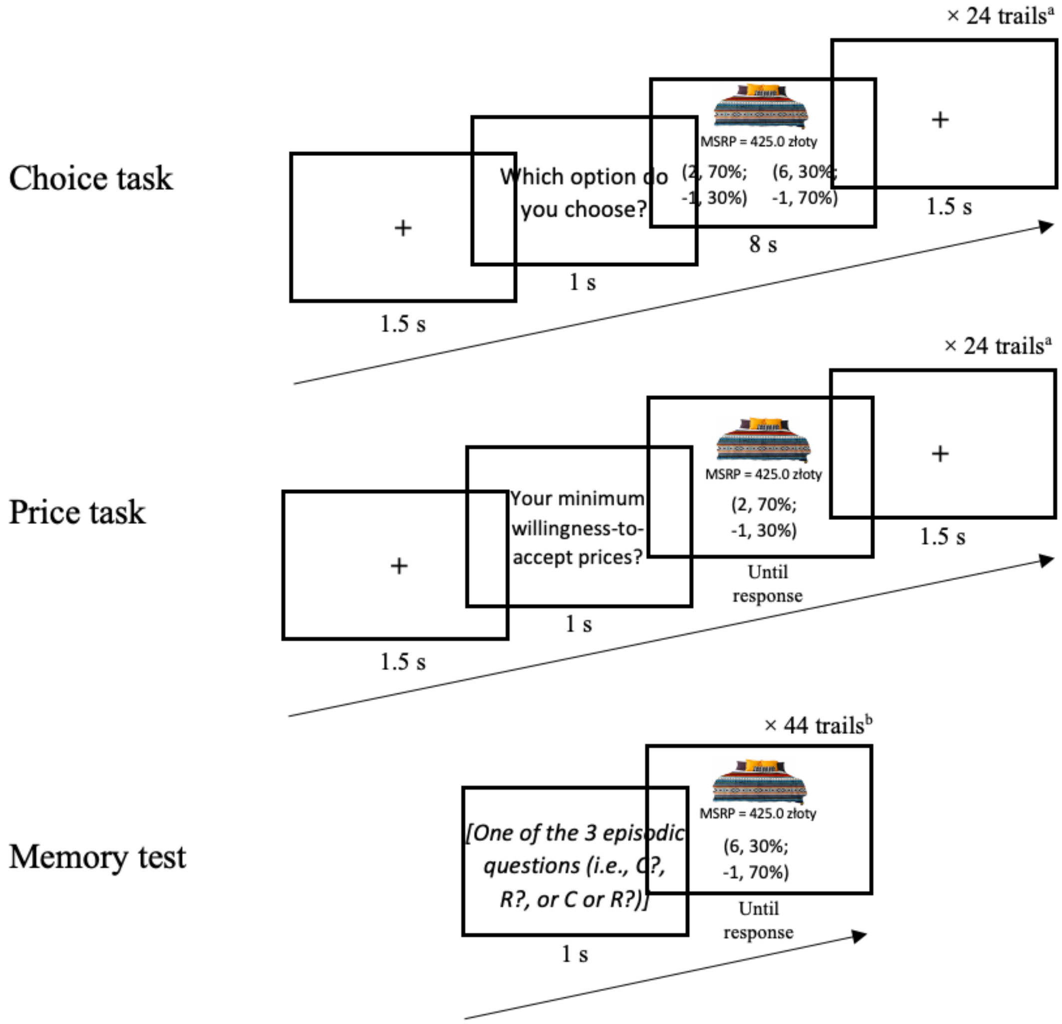


Figure 10: Experimental procedure.
Note: Timeline of the experiment includes three blocks: the choice task, the price task, and the memory test. A trial started with a fixation point, (1) followed by the presentation of two options on the screen for 8 seconds within the choice task and (2) followed by the presentation of one option on the screen until the participants entered their willingness-to-accept price within the price task. In the memory test, only one option was presented each time on the screen. Then, a next option would be presented after the participants entered their answer to one of the episodic memory questions for a previous option. [a]Within the choice and price tasks, the 24 trials consisted of one pair of the filler options in the beginning trial and another pair in the end trial as buffers in order to avoid the primacy and recency effects. [b]In the memory test, the 44 trials consisted of 22 target and their paired 22 distractor options.

Times New Roman 32-point font underneath the mutual product's image, and displayed for 8 seconds. The question "Which option do you choose?" was also presented underneath the bet options on the same slide. All the participants were requested to choose only one option that they would like mostly in each pair. In the second "price task" block, each pair of options were presented and evaluated consecutively in the next slides.

In the third "memory test" block, either a target option was presented for the second time, or a distractor option was presented for the first time. Every trial showed one of the three episodic memory questions (i.e., *C?*, *R?*, *C or R?*) in black 36-point font underneath the bet option and was displayed for 8 seconds. The participants were instructed to respond according to their recollections to these questions by pressing the following keys on a computer keyboard: "T" for "yes" (in Polish "tak") or "N" for "no" (in Polish "nie"). All the target and distractor options were randomly ordered throughout the three blocks. The participants did not receive any feedback on their decisions. We tested the participants individually in a quiet room, and they finished the study in its entirety. Appendix E.3 shows the detailed instructions that were informed to the participants.

7.5. Results

In the following, we first consider whether PR was observed, and if it was, under what conditions. We pooled across the same loss ratios and, similar to Experiment 1: Magnitude effects in PR, across the low and high loss or gain ratios. The detailed results of the binomial tests on the percentages of choice, price valuation, and predicted and unpredicted PR are shown in Table 8. Specifically, we compute each gain ratio by means of arithmetic average over each affiliated lotteries (e.g., $\text{Ratio}_{\text{Bets 3 - 5}} = \dfrac{3.0 + 4.3 + 8.0}{3} = 5.1$). The proportionate rates of predicted and unpredicted PR are reported in these entries corresponding to "P-bet" and "\$-bet > P-bet" and to "\$-bet" and "P-bet > \$-bet", respectively. The results of the binomial tests are shown in the "*p*-value" and "*g*" entries.

Second, we elucidate the source discrimination of targets and distractors to examine whether the judgments were accurate. Third, we consider the extent to which correct memory responses were observed under different PR types. Overall, the resulting data provide

Table 8: Percentages of choice, price valuation, and predicted and unpredicted PR: Exact two-sided binomial tests pooled across the same loss ratios and across the low and high loss or gain ratios.[a] (continued)

Lotteries 3 - 5 (loss ratio = -1.0; gain ratio = 5.1):

Price	Choice (%) P-bet	$-bet	Total
P-bet > $-bet	15.11	15.11	30.22***
$-bet > P-bet	19.79	32.81	52.60***
P-bet = $-bet	7.81	9.37	17.18
Total	42.71	57.29	
p-value	.051	< .001	.328
g	0.07	0.14	0.07

Lotteries 6 - 8 (loss ratio = -2.0; gain ratio = 9.4):

Price	Choice (%) P-bet	$-bet	Total
P-bet > $-bet	13.54	15.10	28.64***
$-bet > P-bet	21.36	37.50	58.86***
P-bet = $-bet	6.77	5.73	12.50
Total	41.67*	58.33*	
p-value	.025	< .001	.188
g	0.08	0.17	0.09

Lotteries 9 - 12 (loss ratio = -3.0; gain ratio = 8.3):

Price	Choice (%) P-bet	$-bet	Total
P-bet > $-bet	14.06	14.06**	28.12***
$-bet > P-bet	27.35**	28.91	56.26***
P-bet = $-bet	6.64	8.98	15.62
Total	48.05	51.95	
p-value	.574	< .001	.001
g	0.02	0.17	0.16

Lotteries 13 - 15 (loss ratio = -4.0; gain ratio = 13.6):

Price	Choice (%) P-bet	$-bet	Total
P-bet > $-bet	13.54	11.46**	25.00***
$-bet > P-bet	23.96**	39.06	63.02***
P-bet = $-bet	4.69	7.29	11.98
Total	42.19*	57.81*	
p-value	.036	< .001	.005
g	0.08	0.21	0.18

Lotteries 16 - 19 (loss ratio = -6.0; gain ratio = 17.9):

Price	Choice (%) P-bet	$-bet	Total
P-bet > $-bet	14.06	9.76***	23.82***
$-bet > P-bet	34.77***	28.91	63.68***
P-bet = $-bet	5.08	7.42	12.50
Total	53.91	46.09	
p-value	.235	< .001	< .001
g	0.04	0.23	0.28

Lotteries 20 - 21 (loss ratio = -8.0; gain ratio = 35.0):

Price	Choice (%) P-bet	$-bet	Total
P-bet > $-bet	21.09	7.81***	28.90***
$-bet > P-bet	28.91***	32.03	60.94***
P-bet = $-bet	3.91	6.25	10.16
Total	53.91	46.09	
p-value	.426	< .001	< .001
g	0.04	0.18	0.29

Lotteries 22 - 24 (loss ratio = -10.0; gain ratio = 28.6):

Price	Choice (%) P-bet	$-bet	Total
P-bet > $-bet	22.40	8.85***	31.25***
$-bet > P-bet	38.02***	18.75	56.77***
P-bet = $-bet	7.29	4.69	11.98
Total	67.71***	32.29***	
p-value	< .001	< .001	< .001
g	0.18	0.15	0.31

Lotteries 3 - 15 (-4.0 ⩾ loss ratio ⩾ -1.0; 13.6 ⩾ gain ratio ⩾ 5.1):

Price	Choice (%) P-bet	$-bet	Total
P-bet > $-bet	14.06	13.94***	28.00***
$-bet > P-bet	23.44***	34.13	57.57***
P-bet = $-bet	6.49	7.93	14.32
Total	43.99***	56.01***	
p-value	< .001	< .001	< .001
g	0.06	0.17	0.13

Lotteries 16 - 24 (-10.0 ⩾ loss ratio ⩾ -6.0; 35.00 ⩾ gain ratio ⩾ 17.9):

Price	Choice (%) P-bet	$-bet	Total
P-bet > $-bet	18.40	9.03***	27.43***
$-bet > P-bet	34.55***	26.21	60.76***
P-bet = $-bet	5.56	6.25	11.81
Total	58.51***	41.49***	
p-value	< .001	< .001	< .001
g	0.09	0.19	0.29

Lotteries 3 - 24 (-10.0 ⩾ loss ratio ⩾ -1.0; 35.00 ⩾ gain ratio ⩾ 5.1):

Price	Choice (%) P-bet	$-bet	Total
P-bet > $-bet	15.84	11.93***	27.77***
$-bet > P-bet	27.98***	30.90	58.88***
P-bet = $-bet	6.11	7.24	13.35
Total	49.93	50.07	
p-value	.979	< .001	< .001
g	0.00	0.18	0.20

[a] (1) The three binomial p-values in each of the combined lotteries show, from left to right, the test statistics of the choice, price valuation, and predicted versus unpredicted PR rates, respectively. (2) Within the price task, we calculate the exact binomial tests by excluding the equal valuation percentages. The reason, of course, is that according to standard theory, the strict preference, choosing Bet A over Bet B, is inconsistent with the deviating valuation price, that is, pricing Bet B over Bet A, and indifference, that is, pricing Bet A and Bet B equivalently. (3) According to Cohen (1988), a rule of thumb for the effect size of g is as follows: 0.00 < 0.05 — Negligible; 0.10 < 0.15 — Small; 0.20 < 0.25 — Medium; 0.25 or more — Large.

* $p < .05$; ** $p < .01$; *** $p < .001$.

observed behavior of the 64 participants indicating choice preferences, stated valuation prices, and recognition memory over 22 target gamble pairs and their corresponding 22 distractor pairs——(a) 22 choices over gamble pairs and (b) 44 valuation prices and 44 memory probes over individual gambles.

7.5.1. The choice task

The binomial tests show, on the one hand, that for the lotteries nos. 3 - 15, which have low loss or gain ratios from -1.0 to -4.0 or from 5.1 to 13.6, respectively, the percentage that the \$-bets were chosen (M = 56.01%, SD = 20.85%) was significantly larger than the percentage that their paired P-bets were chosen (M = 43.99%, SD = 20.85%), $p < .001$, g = 0.06. On the other hand, for the lotteries nos. 16 - 24, which have high loss or gain ratios from -6.0 to -10.0 or from 17.9 to 35.0, respectively, the percentage that the P-bets were chosen (M = 58.51%, SD = 16.75%) was significantly larger than the percentage that their paired \$-bets were chosen (M = 41.49%, SD = 16.75%), $p < .001$, g = 0.09 (see Table 8; cf., Figure 11). Generally speaking, when loss divergences between paired P-bets and \$-bets are no more than, in the present experiment, a -4.0:1 ratio, risk-seeking than risk-averse preference is more significant. By contrast, when loss divergences between paired P-bets and \$-bets are no less than, in the present experiment, a -6.0:1 ratio, risk-averse than risk-seeking preference is more significant. Thus, both Hypothesis 1.a and Hypothesis 1.b were reconfirmed. Summing across these combined loss or gain ratios, the binomial tests show a monotonic risk preference between the P-bets and \$-bets at the loss or gain ratios between -4.0 and -6.0 or 13.6 and 17.9, respectively, where the participants switched their preference from risk seeking to risk averse or vice versa.

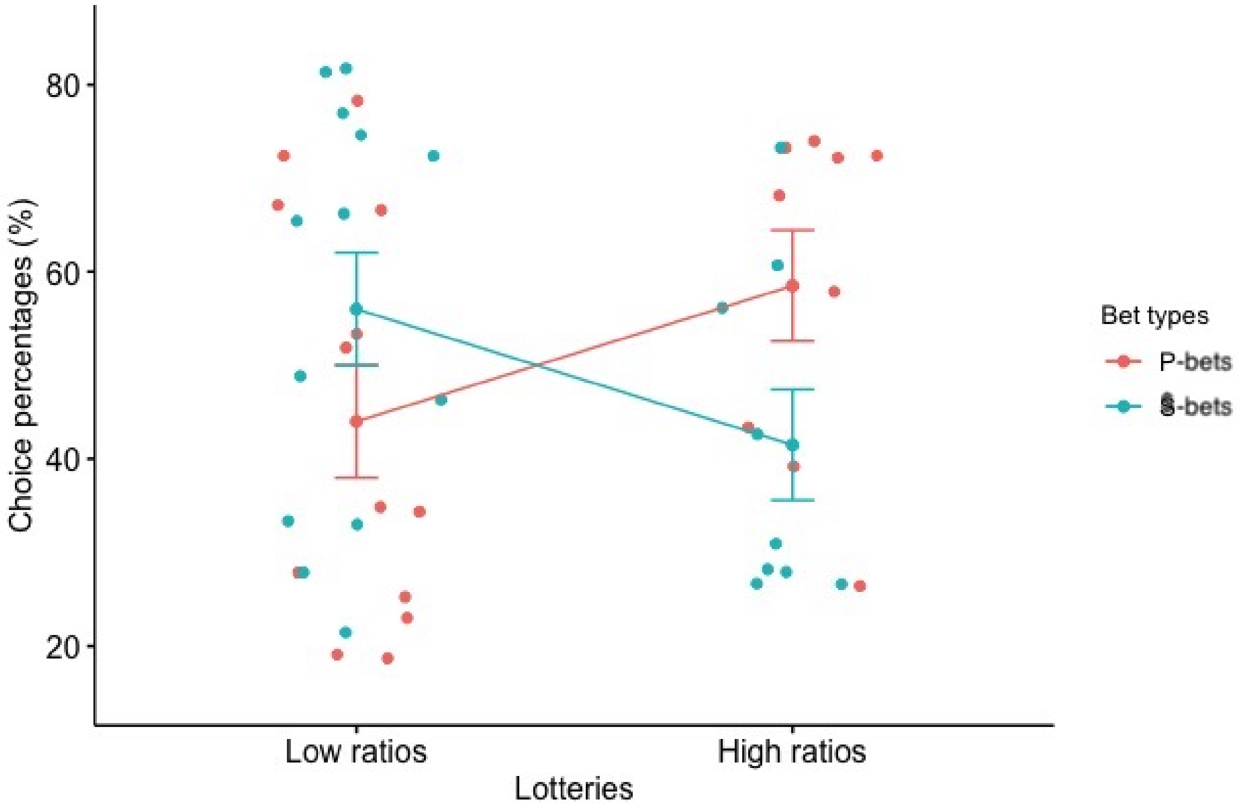
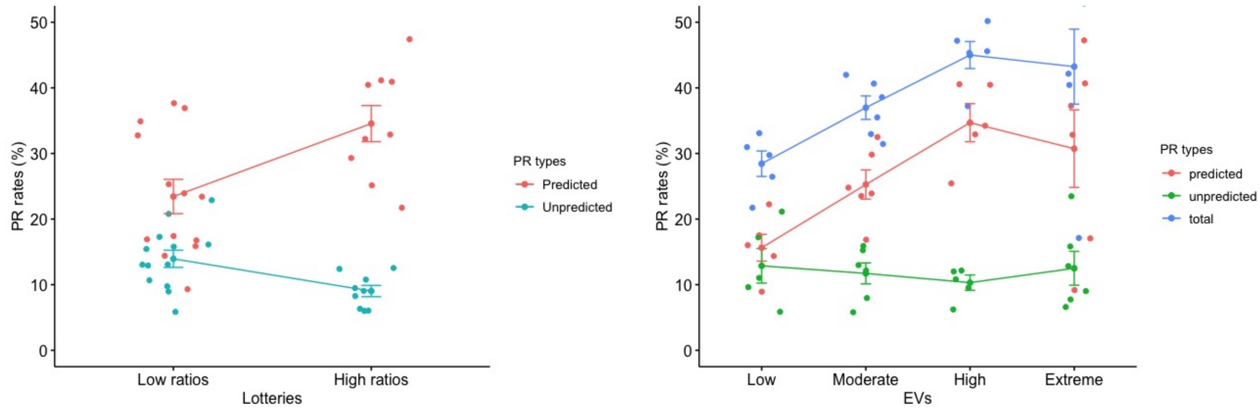


Figure 11: Percentages of choosing P-bets and $-bets by lottery group with low (Nos. 3 - 15) versus high (Nos. 16 - 24) loss or gain ratios.
Note: Error bars are the ±1 standard error of the mean.

7.5.2. Predicted and unpredicted PR

We replicated again the PR phenomenon, as indicated by predicted PR being more frequent than unpredicted PR (see Table 8). Moreover, we also reconfirmed that loss ratios of bet pairs determine predicted and unpredicted PR (Hypothesis 2.a and Hypothesis 2.b). More specifically, pooled together the lotteries nos. 3 - 15 and the lotteries nos. 16 - 24, which have low and high loss or gain ratios, respectively, Wilcoxon signed-rank tests with continuity corrections show, on the one hand, that the predicted PR rates of the latter lotteries (M = 34.55%, SD = 8.25%, Q1 = 29.69%, Q3 = 40.63%) significantly outnumbered these of the former lotteries (M = 23.44%, SD = 9.44%, Q1 = 17.19%, Q3 = 32.81%), $z = 2.31$, $p =$ .021, $d = 0.64$. On the other hand, the unpredicted PR rates of the lotteries nos. 3 - 15 with low loss or gain ratios (M = 13.94%, SD = 4.71%, Q1 = 10.94%, Q3 = 15.63%) significantly outnumbered these of the lotteries nos. 16 - 24 with high loss or gain ratios (M = 9.03%, SD = 2.57%, Q1 = 6.25%, Q3 = 10.94%), z = 2.04, p = .042, d = 0.56 (see Figure 12a).



(a) (b)

Figure 12: Predicted and unpredicted PR rates by lottery group with low (Nos. 3 - 15) versus high (Nos. 16 - 24) loss or gain ratios (left panel) and with low versus moderate versus high versus extreme EVs (right panel).
Note: Right panel: Low—4.4 to 8.4 PLN; Moderate—24.0 to 84.0 PLN; High—467.5 to 1200.0 PLN; Extreme—1550.0 to 2800.0 PLN. Error bars are the ±1 standard error of the mean.

Pooled together the lotteries with low, moderate, high, and extreme EVs, pairwise comparisons using Wilcoxon signed-rank tests with corrections of the Benjamini-Hochberg method indicate that, on the one hand, though all weaker, (1) the predicted PR rates of those lotteries with *moderate* EVs (M = 25.26%, SD = 5.45%, Q1 = 23.44%, Q3 = 28.52%) and *high* EVs (M = 34.69%, SD = 6.48%, Q1 = 32.81%, Q3 = 40.63%) outnumbered the predicted PR rates of those lotteries with *low* EVs (M = 15.63%, SD = 4.56%, Q1 = 14.06%, Q3 = 17.19%), z = 1.56, p = .120, d = 0.33; (2) the predicted PR rates of these lotteries with *high* EVs outnumbered the predicted PR rates of these lotteries with *moderate* EVs, z = 1.56, p = .120, d = 0.33; and (3) the predicted PR rates of these lotteries with *extreme* EVs (M = 30.72%, SD = 5.91%, Q1 = 21.09%, Q3 = 39.84%) outnumbered the predicted PR rates of these lotteries with *low* and *moderate* EVs, z = 1.53, p = .130, d = 0.33. On the other hand, the unpredicted PR rates among all the groups were not significantly different between each other (all *ps* $>$ .880) (see Figure 12b). Taken together, these results indicate a somewhat consistent but non-significant difference in predicted PR as a function of EVs. Therefore, Hypothesis 5 was not confirmed although plausible.

Table 9 summarizes the individual-level results in total (the upper two panels), at the low loss or gain ratios (the third panel), and at the high loss or gain ratios (the lower panel). Overall, it indicates that many participants demonstrated predicted or unpredicted PR across some, albeit not all, lotteries. More specifically, the first numerical column in the upper panel of the table shows that 92%, 70%, and 97% of the participants in total respectively exhibited predicted PR, unpredicted PR, and predicted or unpredicted PR for at least one lottery. As can be seen, almost all the participants demonstrated either predicted or unpredicted PR. The next twenty-two columns give the percentages of the participants who violated in such a way over only one lottery until over eighteen lotteries. These results show that it tends to be relatively rare for a participant to violate PR consistently at every opportunity.

The first numerical column in the third panel of the table shows that 70%, 56%, and 94% of the participants at the *low* loss or gain ratios respectively exhibited predicted PR, unpredicted PR, and predicted or unpredicted PR for at least one lottery. Only 6% of the participants never demonstrated either predicted or unpredicted PR. The first numerical column in the lower panel of the table shows that 83%, 41%, and 94% of the participants at the *high* loss or gain ratios respectively exhibited predicted PR, unpredicted PR, and predicted or unpredicted PR for at least one lottery. Only 8% of the participants never demonstrated either predicted or unpredicted PR. In sum, these results support Hypothesis 2.a and Hypothesis 2.b and suggest that PR can be attenuated when lotteries have low

Table 9: Individual-level incidences of violation (%).

PR types	Total	n-time violators										
		1	2	3	4	5	6	7	8	9	10	11
Predicted	92	13	11	6	5	3	6	9	8	11	2	5
Unpredicted	70	22	13	8	11	3	2	5	3	0	0	2
Predicted or unpredicted	97	31	27	19	19	9	9	20	17	22	9	11

PR types	n-time violators (continued)										
	12	13	14	15	16	17	18	19	20	21	22
Predicted	3	5	3	0	0	2	2	0	0	0	0
Unpredicted	0	0	0	2	2	0	0	0	0	0	0
Predicted or unpredicted	3	13	3	2	5	2	2	0	0	0	0

PR types	Low loss/gain ratios	n-time violators					
		1	2	3	4	5	6
Predicted	70	36	22	6	6	0	0
Unpredicted	56	34	14	3	5	0	0
Predicted or unpredicted	94	61	45	27	16	2	0

PR types	High loss/gain ratios	n-time violators								
		1	2	3	4	5	6	7	8	9
Predicted	83	20	8	9	14	13	6	11	0	2
Unpredicted	41	23	11	2	0	2	0	2	2	0
Predicted or unpredicted	92	36	27	14	17	22	9	14	3	2

loss or gain ratios, no more than -2.0 or 9.4 at the level of the data.

7.5.3. Source discrimination

In order to determine whether there were any recollection biases, one-sample t-tests with a test value of zero were computed on the frequencies of recollecting a P-bet or \$-bet probe as having been chosen or rejected incorrectly (e.g., choosing the target P-bet but recollecting the distractor P-bet probe as having been chosen). The data show that all the recollection biases were unanimously significantly larger than zero (see Table 10). Further analyses of paired samples t-tests were computed between the frequencies of recollecting a P-bet or \$-bet probe as having been chosen or rejected correctly and incorrectly (cf., Lu and Nieznański, 2020). For the P-bets, the participants remembered more correctly that the target P-bets probes were chosen or rejected. However, they did *not* remember more correctly that the distractor P-bets probes were chosen or rejected. The same pattern was also observed for \$-bets. These results indicate that the participants were not simply guessing on the target P-bets and \$-bets probes, but were guessing on the distractor P-bets and \$-bets probes.

Table 10: Frequencies of recollection biases: One-sample and paired t-tests.

Bet					One-sample t-tests			Paired t-tests		
types	Probe types	Total	M	SD	$t(63)$	p	d	$t(63)$	p	d
P-bets	Targets	11	4.27	2.03	16.85***	< .001	2.11	4.78***	< .001	0.60
	Distractors	11	6.17	2.14	23.05***	< .001	2.88	-2.52*	.014	-0.32
\$-bets	Targets	11	4.31	1.94	17.76***	< .001	2.22	5.01***	< .001	0.63
	Distractors	11	5.42	2.18	19.89***	< .001	2.49	0.32	.753	0.04

* $p < .05$; *** $p < .001$.

7.5.4. Recollection-based responses

To identify retrieval effects on PR, we calculated correct recollection rates as $\frac{\text{hit}}{\text{total response}}$ per PR type (PR vs. equivalent vs. non-PR) for each participant. Table 11 shows the descriptive findings of the mean correct recollection rates. Paired samples t-tests reveal that even though at only chance levels, the mean correct recollection rates increased for non-PR than PR, $M_\Delta = 12.88\%$, $SE = 3.99\%$, $t(61) = 2.95$, $p = .005$, $d = 0.55$. The results indicate that there was evidence of episodic memory in PR, such that people seem likely to recollect bets more correctly when they exhibit a consistent preference than when they exhibit PR. Thus, Hypothesis 7 was confirmed.

Table 11: Mean correct recollection rates per PR types.

PR types	*M* (%)	*SD* (%)
PR[a]	48.22	22.52
Equivalent	57.24	36.50
Non-PR	61.10	23.61

[a] The correct recollection rates under the PR condition were calculated for each participant by averaging the correct recollection rates across the predicted and unpredicted conditions.

7.6. Discussion

The current study, first, extends previous limited research on trade-off magnitude PR, examining how EVDs between bet pairs affect rates of predicted and unpredicted PR. The results indicate several trends in the same direction such that lower EVs serve to dampen the tendency towards gross overpricing $-bets, and hence to reduce predicted PR. Conversely, higher EVs serve to elicit predicted PR so long as they reach the moderate EV, that is, no less than 24.0 PLN at the level of the data. Although the results indicated a lack of statistical significance, the observed predicted than unpredicted PR increased for these lotteries with moderate and high EVs since the percentage of the participants choosing P-bets increased, instead of that the percentage of the participants evaluating $-bets higher than P-bets increased. This implies that the ideal lottery for observing predicted PR would have a larger variance of payoffs between bet pairs (facilitating choice of the P-bet). The existing studies have observed that a market-like mechanism may, with some success, reduce the rate of PR (Braga et al., 2009; Chai, 2005; Gunnarsson et al., 2003). The experiment reported here sharpens up the evidence as for how the EV magnitude shows an important impact on the rates of predicted PR. This pattern, we argue, is strong evidence of the context-dependent nature of PR as ubiquitously influenced by loss aversion.

Second and foremost, contrary to decades of experimentation in PR studies, which have variously gauged that PR systematically violates formal logic theories, researchers have paid almost no attention to any memory-related explanations that are correlated with PR. For this reason, past PR studies that assess whether memory plays a role in PR have been rare. The current study attempted, for the first time, to demonstrate that there is direct evidence of episodic memory in PR, such that individuals exhibit less PR when they are able to retrieve their initial choices. Therefore, PR, which has customarily been explained as biased judgments or inconsistent risk preferences at large, may be partly due to incorrect memory retrieval.

The different patterns that we observed between P-bet and $-bet preferences within choice and price tasks may be, in some way, connected with a different level of processing imposed by each type of tasks. More specifically, choice tasks are assumed as eliciting a less effortful, albeit different, cognitive process than price tasks. The mental representations formed by this process can be contextually sensitive to the qualitative rather than to quantitative scale (Fisher and Hawkins, 1993), or more precisely, to probability or payoff attribute (Slovic and Lichtenstein, 1983; Zhou et al., 2018) rather than to option-based information searches within price tasks (Hinvest et al., 2014; Zhou et al., 2016).

It seems that individuals rely more on a gist level of processing within choice tasks because choices are general and categorical; whereas, individuals are elicited to rely on a more verbatim level of processing within price tasks because they have to declare a certain amount of money for paired bets. As a result, the prominent “gist” representations within choice tasks, which may mainly focus on the salient domain of probability, might explain the finding that the participants were likely to discriminate sources stemmed from the targets more correctly than those from the distractors by virtue of drawing attention toward the only different attribute of probability, where the targets were superior to the distractors. By contrast, the prominent “verbatim” representations within price tasks elicit a precision on the comparison of whole bet pairs. Likewise, this premise is similar to the distinction between Type 1 (intuitive, pragmatic, or fast) and Type 2 (reasoned, rational, or slow) processes in dual dichotomy of decision-making theories (Kahneman, 2003). There are also similarities between these dual systems and that evoked by intuitive and affect-based heuristics for hedonic goods when preferences are expressed through choices as compared to willingness to pay for utilitarian goods which engenders consideration and synthesis of various information (O’Donnell and Evers, 2019).

8. Experiment 4: Episodic memory in attraction effect PR

The goals of the present experiment were to test whether (1) EVDs between target and competitor bets within a given bet pair affect attraction effect PR (Hypothesis 6); and (2) correctly identifying initial choice preferences of bets can ameliorate predicted and unpredicted PR (Hypothesis 7). The attraction effect occurs when an irrelevant option is added to a choice set and then changes preference between existing options of the set. Subjects were paid both a show-up fee and a play-out fee to make conventional lottery choice and evaluation tasks as well as a novel choice recall test. Additionally, we added a noun to each choice problem as a memory cue. The difference between the EVs of the lotteries was varied across the lottery choice problems to retest the hypothesis that was put forward by Farmer et al. (2017) in a gain-loss design.

8.1. Participants

Due to COVID-19, we collected data for this experiment through an online survey by means of questionnaires in PDF format. To recruit participants, we sent invitation emails to the student body including undergraduate and graduate students and doctoral candidates at Cardinal Stefan Wyszyński University in Warsaw, as well as to people from the author's social networks. We motivated participation by offering monetary reward of 50 PLN as a base compensation for each participant. We offered semi-contingent (half of the base compensation, that is, 25 PLN, was promised to be paid upon compliance), relatively large incentives since one mechanism by which choice may enhance episodic memory is by increasing the monetary reward of alternative items (e.g., Miendlarzewska, Bavelier and Schwartz, 2016; Schwartz and Efklides, 2012).

Moreover, this so-called "payment" (incentives) effect was also combined with another "play-out" effect in that the participants were compensated for their "show up" and had opportunities to win a bonus of 25 PLN in a raffle based on the price of a randomly chosen bet they made during the experiment (outlined below). We used this raffle as a supplementary incentive for each participant because played-out gambles or real consequences are more likely to elicit stable preferences (Berg et al., 2013). The payments and bonuses were made as online shopping cards from a Polish commercial retailer. Once receiving acknowledgment of the participation, we sent participants the questionnaires by email.

A total of 86 native speakers of Polish, aged between 18 and 60 years (M = 28.9, SD = 9.3; the female percentage was 59.30%), volunteered to complete the experiment. The average additional earning to the participants was 3.2 PLN (SD = 6.0 PLN) with 0 PLN being the lowest and 25 PLN being the highest payment. Each invited participant was assigned a unique QR code, which ensured that (1) only invited participants could take part in the experiment, and (2) none of participants can take part more than once.

8.2. Materials

The materials consisted of 24 triplets of bets as targets, competitors, and attraction decoys (Nos. 1 - 24), another 4 triplets of bets as buffers (Nos. 25 - 28), remaining 24 bets as distractors (Nos. 29 - 52), as well as their corresponding 108 unique words (see Appendix D.5). The attraction decoy, as its name suggests, has the same gain and loss payoffs as its target but the less attractive probability distributions to it. The context effect of the attraction decoy presumably engenders the target bet to be chosen more often and to be priced more highly than the competitor bet. All the bets were modest monetary gambles containing the attributes of probabilities and gain and loss payoffs, and each bet was different from one another at least in one aspect of probability, gain, and loss.

Both the probabilities and gain and loss payoffs of the bets were visualized in a more explicitly perceptual manner partially taken from Farmer et al. (2017) (see Figure 13). The graphical representation involved three blocks of squares in 10 by 10 grids with sectors colored in green, blue, and red, whose numbers were proportional to the probability of winning the gain payoff and the gain and loss payoffs, respectively. Additionally, in order to help the participants to improve memory for bets and decisions, we added a unique word for each bet, as shown on the upper left of red squares in the bottom row. According to Craik and Lockhart (1972), more semantically based word processing can lead to much "deeper" subsequent acquisition in long-term memory than "shallow" visual processing. Therefore, each bet was identified by a specific combination of the densities of green, blue, and red squares and a word.

More specifically, each of the decoy bets was paired with only one pair of target and competitor bets, and each of the unique words co-occurred with only one target, competitor, decoy, buffer, or distractor bet. Moreover, half of the decoy bets were paired with half of the target P-bets, and the remaining half with the rest half of the target $-bets. The target P-bets ($-bets) were given the fixed probabilities of 70%, 75%, 80%, or 85% (20%, 25%, 30%, 35%, or 40%) for gains and their respective rest probabilities for losses. The decoy bets were always of the same payoffs as their target bets but with 15% lower probability (rounded off to zero decimal place). This manipulation presumably enables an attribute (e.g., probability) that is relatively more difficult to evaluate becoming the one that is relatively more easily to evaluate after a decoy bet is added.

The EVDs within the pairs of target and competitor bets had the following five levels: (1) 0% (Nos. 1 - 8), denoting no difference; (2) 50%(↓) (Nos. 9 - 12), denoting the EV of the P-bet 50% lower than the EV of the $-bet; (3) 50%(↑) (Nos. 13 - 16), denoting the EV

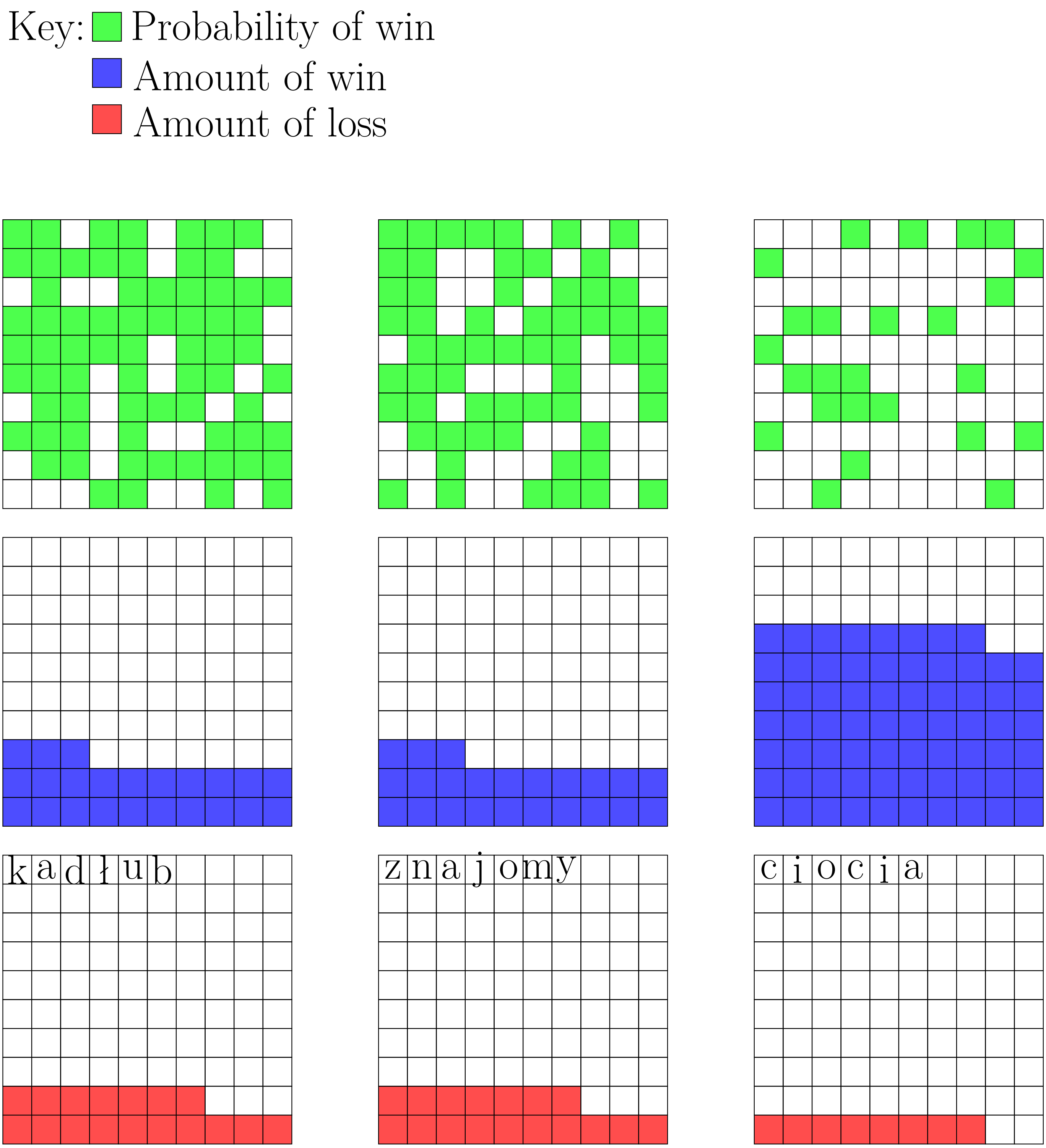


Figure 13: The representation of lotteries during the choice and price tasks and the memory test.
Note: This example shows a target P-bet on the left side, an attraction decoy P-bet in the middle, and a competitor $-bet on the right side. The decoy bet was always posited on the closest right side of the target bet. The densities of green squares (top block), blue squares (middle block), and red squares (bottom block) represented the probability of winning the gain payoff and the gain and loss payoffs of the bet, respectively. Each column represented an alternative bet.

Choose: ☐ Choose: ☐ Choose: ☐

(a) Choice task

Price: ☐ Price: ☐ Price: ☐

(b) Price task

Did you choose the bet?

[or]

Did you reject the bet?

[or]

Did you choose or reject the bet?

Yes: ☐ No: ☐

(c) Memory test

Figure 13: The representation of lotteries during the choice and price tasks and the memory test. (continued) *Note*: (a) Within the choice tasks, the participants were asked to choose only one bet among each of three bets at any one time by ticking the appropriate box beneath this chosen bet. (2) Within the price tasks, the participants were asked to indicate their willingness-to-accept (smallest) price from the seller's viewpoint by entering this amount in the blank box beneath each bet. (3) In the memory test, only one bet and one question were given on each page, and the participants were asked to recall their choices or rejections made within the choice task. The participants had two possible responses, shown here.

of the P-bet 50% higher than the EV of the \$-bet; (4) 100%(↓) (Nos. 17 - 20), denoting the EV of the P-bet 100% lower than the EV of the \$-bet; and (5) 100%(↑) (Nos. 21 - 24), denoting the EV of the P-bet 100% higher than the EV of the \$-bet. The manipulations of EVD within bet pairs allowed us to test Hypothesis 6.

8.3. Design

We designed a similar source memory paradigm as in Experiment 3: Episodic memory in PR. More precisely, a within-subjects design was used. Each of the choice and price tasks was presented once with either a P-bet or a $-bet as the target, resulting in 28 unique sets for either the choice or price task. At the same time, each of the attraction decoys was also manipulated for one time. The decoy position defined whether a P-bet or a $-bet was the target. The memory test contained (1) 6 target P-bets ($-bets) with 2 *C?* questions, 2 *R?* questions, and 2 *C or R?* questions; (2) 6 competitor P-bets ($-bets) with 2 *C?* questions, 2 *R?* questions, and 2 *C or R?* questions; (3) 12 attraction decoy P-bets ($-bets) with 4 *C?* questions, 4 *R?* questions, and 4 *C or R?* questions; and (4) 12 distractor P-bets ($-bets) with 4 *C?* questions, 4 *R?* questions, and 4 *C or R?* questions, in which *C?*, *R?*, and *C or R?* denote the episodic memory questions "Did you choose the bet?", "Did you reject the bet?", and "Did you choose or reject the bet?", respectively (see Table 12). Once again, we manipulated these distractor bets and questions in order to re-examine Hypothesis 7. Besides, we used three versions of the questionnaire in order to counterbalance the three types of the episodic memory questions, such that each particular bet was presented with *C?*, *R?*, and *C or R?* to an approximately equal number of the participants.

In total, the experiment was divided into three sessions of 128 trials per participant. The presentation of the trails of the three sessions was completely randomized with the exception that the Nos. 25 and 26 buffer bets were always presented at the beginning of the choice task, and the Nos. 27 and 28 buffer bets were always presented at the end of the price task. This control was added in order to avoid the primacy and recency effects. Moreover, joint evaluation was used across the choice and price tasks; that is, participants could view three

Table 12: Numbers of episodic memory questions in the memory test.

Bet types	Probe types	Questions[a] *C?*	*R?*	*C or R?*	Total
P-bets ($-bets)	Targets	2	2	2	6
	Competitors	2	2	2	6
	Decoys	4	4	4	12
	Distractors	4	4	4	12
	Total	12	12	12	36

[a] *C?* = "Did you choose the bet?"; *R?* = "Did you reject the bet?"; *C or R?* = "Did you choose or reject the bet?".

bets at a time within the choice and price tasks. This enabled the participants to assess alternative bets by making a perceptual comparison of the visual density of the different displays, encouraging them to encode the three bets' information distinctively. A separate evaluation mode was used as the presentation of the tasks and bets in the memory test in which the participants viewed bets one-at-a-time.

In order to avoid subject overvaluations of the bets, we used two incentive-compatible elicitation procedures to measure willingness-to-accept prices, known as the Becker-DeGroot-Marschak (BDM) method (Becker, DeGroot and Marschak, 1964) and the random lottery incentive system (Starmer and Sugden, 1991). In an experiment that uses the former method to elicit a selling price or an approximate certainty equivalent for the P-bet = (80%, 25; 20%, -20), for example, subjects are prompted to state a minimum amount of bid for which they would sell the investment, say, x PLN. Once they have decided upon the x PLN, a number between zero and the largest possible outcome of the investment——in this case, 25 PLN——is obtained through a random number generator. If the x PLN is less than the random number, subjects sell the P-bet for the price indicated by the x PLN. If the x PLN is equal to or greater than the random number, subjects would be required to keep the P-bet.

In an experiment that uses the random lottery incentive system, subjects perform a series of trials, knowing exactly from the start that one trial will be chosen at random to be played out for real at the end of the experiment. This mechanism is often used because it is effective in ensuring the independence of actions across trials, while allowing for real-world consequences of decisions. Although both the procedures, especially the BDM method, were not obviously acquainted by the most participants, the mechanism of stating the true valuation of the bet and a randomly selected bet at the end were explained in detail in the instruction, using an example bet that was not part of the experimental trials (see Appendix E.4 for the full instruction). We instructed them to read carefully before they started to bid, in that it was in their own best interests to state the minimum amounts at which they would indeed sell the bets.

Consequently, it is possible that the participants could revisit their previous choice preferences when answering the episodic memory questions in the memory test. However, there is no reason to believe that the participants were either likely or motivated to do so due to three reasons. First, it was emphasized in bold font in the instruction that the participants must work through the questions sequentially, from the first page to the last page, and not to skip ahead or back. Second, the participants were also instructed that the total "show-up" remuneration and additional earnings were entirely independent of their performance in the memory test. Instead, their chance to win the additional earnings in the raffle was dependent only partly on the willingness-to-accept price of a randomly selected bet and partly on chance determined by the BDM method. Third and technically speaking, if the participants attempted, by using the Find toolbar or the Search window, to run searches to find specific stimuli (e.g., the words corresponding to the lotteries), our PDF questionnaires did not provide any valid results that could match the search terms.

Research investigating the practice of memory of previously studied information (i.e., memory retrieval) typically involves such a study phase in which interitem interval and interstimulus interval (ISI) are fixed. For instance, in a recognition memory experiment, words in a list may be presented at a 4-sec rate, with ISIs (blank) of 250 ms (e.g., Lu and Nieznański, 2020). However, the study phases of the current experiment involved completing the choice and price tasks, which usually require an until response control instead of a constant-interval control, in order to reveal the relation between levels of stimulus processing and memory for those processed bets. That is, having selection and evaluation periods as long as needed for making decisions ensures that presentation of the stimuli during the two periods can influence context-dependent processes of ranking bets and assigning values enough to have an impact during memory retrieval.

Real-world research must deal with real-world events. Compared with subjects in controlled lab-based settings, people in everyday life are usually not restricted to rigorously limited time for making consequential judgments and remembering retrospective components. We believe that the ready source of our PDF questionnaires can provide complementary data to laboratory studies to test for attraction effect PR in subjective preferences. Empirical investigations into the real-world gambling behavior in Las Vegas (Lichtenstein and Slovic, 1973) and into people's opinions on a wide variety of topics in a crowd-sourced website (Lee and Ke, 2022) have also shown naturally occurring evidence for PR. Thus, either according to the experimental requirements or the perspective of cognitive ethology (Kingstone, Smilek and Eastwood, 2008), the skipping of the temporal control seems to be the most natural solution in this context.

8.4. Procedure

At the beginning of the experimental session, the participants read a three-page instruction, which explained clearly the rules and the incentive compatibility of the BDM method. They were also instructed to complete the three sessions consecutively, first the choice task, then the price task, and finally the memory test. The experiment lasted approximately between 25 and 45 minutes according to the feedback from the participants. The time varied across the participants because they explicitly proceeded at their own pace. After a participant had completed the experiment, one bet was selected randomly and played out in the raffle.

8.5. Measures

We used two measures to determine the presence of contextual PR. First, in order to examine whether there were any effects of EVD on attraction effect PR, following the literature (e.g., Huber et al., 1982; Pettibone and Wedell, 2007; Ronayne and Brown, 2017; Soltani et al., 2012; Wedell, 1991), we computed the contextual PR rate (1) by subtracting the proportion of competitor choices from the proportion of target choices within the choice task; and (2) by subtracting the proportion of competitor bets which were priced higher from the proportion of target bets which were priced higher within the price task. A positive rate indicates that the participants preferred the target bet more often than the competitor bet. A negative rate indicates that the participants preferred the competitor bet more often than the target bet. No difference indicates that the participants preferred the target bet and the competitor bet the same number of times.

The contextual PR rates for different EVD conditions are aggregate data of all the participants. Then, a *group* level contextual PR rate can be calculated.[3] We detect the contextual PR rates between different EVD conditions by means of two-tailed one-sample t-tests. Second, in order to examine whether there were any biased probability judgments of target cues in the memory test, following the method used in Experiment 3: Episodic memory in PR, we computed predicted and unpredicted PR.

8.6. Results

8.6.1. Effect of EV on attraction effect PR

To check whether the participants perceived the target bet as superior to the decoy bet, we examined the decoy bet that was chosen and priced higher than the target bet across all the conditions of EVD and expected value level (EVL) for each participant. Within the choice task, 26 participants did not choose any decoy bets, while the rest 60 participants chose the decoy bets instead of the target bets at least once ($M = 2.34$, $SD = 2.73$). Within the price task, 47 participants did not evaluate any decoy bets higher than the target bets, while the rest 39 participants evaluated the decoy bets higher than the target bets at least once ($M = 1.93$, $SD = 3.74$). The proportion of performance within the two tasks differed significantly, $\chi^2(1) = 10.50$, $p = .001$. This echoes those well-acknowledged theories, such as the compatibility hypothesis, which propose that individuals usually elicit a more elaborate level of information processing within the price than choice task (Selart et al., 1999; Tversky et al., 1988).

[3] Another method used in some studies is to calculate *individual* level contextual PR rates by presenting each participant with the same choice and/or price evaluation set many times (e.g., Farmer, Warren, El-Deredy and Howes, 2017; Howes, Warren, Farmer, El-Deredy and Lewis, 2016). Take the choice task for example. The configuration shown in Figure 3 may be presented 10 times over the course of an experiment. We can calculate a rate that option T is chosen from that choice set for each participant. In another 10 trials, each participant would choose from the same choice set but, conversely, with option C as the target and option T as the competitor. Then, we can calculate the contextual PR rate for each participant as the rate that option T is chosen when it is the target minus the rate that option T is chosen when it is the competitor. In this measure, contextual PR rates for different conditions are aggregate data of contextual PR rates for each of the participants.

Eventually, we excluded 14 participants from the analysis of the contextual *choice* PR as their decoy choice rates (M = 7.57, SD = 2.34) exceeded 2.5 times the median absolute deviation (MAD), that is, the median of the absolute deviation from the median ($\text{MAD}_{\text{choice}}$ = 1.50; Leys, Ley, Klein, Bernard and Licata, 2013). Since more than 50%, more precisely, $\frac{47}{86} = 54.65\%$, of the decoy price rate had an identical value (of zero), the $\text{MAD}_{\text{price}}$ was equal to zero. If the MADs-from-median approach were applied, the data of the rest 39 participants whose decoy price rates were larger than zero would then be flagged as outliers, regardless of the level at which we set the outlier cutoff. To resolve this drawback, we put a presumably hard limit of 3 times with reference to the outlier cutoff within the choice task using MAD, a breakdown estimate that the decoy prices exceeded the target prices, on the percentage of points that could be flagged as outliers (Rousseeuw and Croux, 1993). As a result, we excluded 13 participants from the analysis of the contextual *price* PR as their decoy price rates (M = 9.77, SD = 4.19) exceeded this breakdown point.

To analyze the impact of EVD and EVL on contextual PR, we first performed fixed effects linear regression analyses. Table 13 shows the results. In Model 1, we entered all the variables including EVD, EVL, decoy type, age, and gender as well as second-order interaction effects. We did not add education level as a predictor of the incidences of contextual PR, since almost all the participants were either university students or owned at least bachelor degrees. Model 2 was derived using a backward stepwise regression technique with a removal value of p = .05.

Within the *choice* task, the control variable of EVD had the unanticipated effect. There were main effects of EVL and decoy P-bet. The interaction terms suggest that the contextual choice PR rates (1) increased as the EVL rose when the decoy P-bets were added; and (2) decreased as the EVL rose when the decoy $-bets were added. Within the *price* task,

Table 13: Results of fixed effects linear regressions: Contextual PR

	Choice task				Price task			
	Model 1		Model 2		Model 1		Model 2	
Variables	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Intercept	0.68^{***}	0.05	0.65^{***}	0.03	0.36^{***}	0.05	0.36^{***}	0.03
EVD[a]	0.01	0.01			0.01^{*}	0.01	0.01^{*}	0.01
EVL[b]	-0.03^{***}	0.01			-0.01	0.01	-0.01^{*}	0.01
Decoy P-bet	-0.95^{***}	0.05	-0.99^{***}	0.04	-0.72^{***}	0.05	-0.76^{***}	0.05
Age (median split)	-0.02	0.04			0.03	0.05		
Gender	-0.02	0.04			-0.01	0.05		
EVD × EVL	0.00^{*}	0.00			0.00^{*}	0.00		
EVD × Decoy P-bet	-0.01	0.01			-0.04^{***}	0.01	-0.04^{***}	0.01
EVL × Decoy P-bet	0.07^{***}	0.01	0.02^{***}	0.01	0.02	0.01		
EVL × Decoy \$-bet			-0.03^{***}	0.01				

[a] The EVD represents the difference from the target \$-bet minus the target P-bet in a given bet pair.
[b] The EVL represents the EV of the target P-bet.
* $p < .05$; ** $p < .01$; *** $p < .001$.

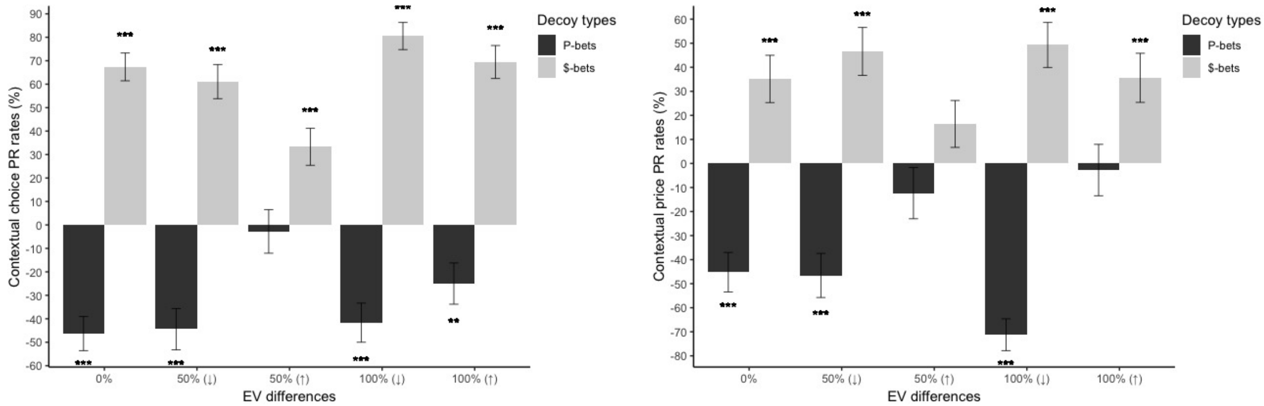
there was a main effect of EVD as predicted and main effects of EVL and decoy P-bet. The interaction term suggests that the contextual price PR rates decreased as the EVDs rose when the decoy P-bets were added. The EVD × EVL interaction effects were only marginally significant in Model 1 and were excluded in the stage-wise Model 2 within both the choice and price tasks. None of the demographic variables was significant in both the models.

8.6.1.1 EVD

Based on the pattern of responding in the PR tasks, when EVDs between target and competitor bets were increased from 0% to 50% and 100%, broadly speaking, the contextual PR rates were not truncated to close to zero. More specifically, a 5 (EVD: 0% vs. 50%(↑) vs. 50%(↓) vs. 100%(↑) vs. 100%(↓)) × 2 (Decoy Type: P-bet vs. \$-bet) repeated measures ANOVA was conducted on contextual choice and price PR rates, respectively. The rates were averaged across the bet pairs for each level of EVD. For EVDs within the *choice* task, there were no main effects (i.e., the contextual PR rates were ubiquitous over conditions), $F(4,\, 284) = 2.32$, $p = .057$, partial $\eta^2 = 0.01$ (see Figure 14a).

For EVDs within the *price* task, there was a significant main effect, $F(4,\, 260) = 6.23$, $p < .001$, partial $\eta^2 = 0.01$. Post-hoc paired t-tests with Bonferroni corrections reveal that when the decoy P-bets were added, the contextual PR rates were markedly truncated from the 0%-magnitude condition to (1) the 50%(↑)-magnitude condition, $M_\Delta = 32.88\%$, $SE = 18.42\%$, $t(73) = 3.71$, $p = .004$, $d = 0.33$; and (2) to close to zero in the 100%(↑)-magnitude condition, $M_\Delta = 42.47\%$, $SE = 8.55\%$, $t(73) = 4.97$, $p < .001$, $d = 0.58$ (see Figure 14b).

Taken together, these results indicate that the contextual PR rates were only truncated in certain, albeit not the majority of, non-0% magnitude conditions. In this respect, the



(a) Choice task

(b) Price task

Figure 14: Contextual PR rates.
Note: As noted, (a) a contextual choice PR rate is measured as the proportion of target choices minus the proportion of competitor choices; and (b) a contextual price PR rate is measured as the proportion of target bets which are priced higher minus the proportion of competitor bets which are priced higher. The ↓ (or ↑) symbol denotes the EV of the P-bet 50% or 100% lower (or higher) than the EV of the $-bet within a given target and competitor bet pair. Error bars are the ±1 standard error of the mean. Asterisks on a given EVD denote that the contextual PR rate was significantly less or greater than zero. $^{**}p < .01$; $^{***}p < .001$ (independent t-tests, two tailed).

present experiment was only partially successful in providing the high degree of reduction when increasing the EVD in contextual PR during task development as Farmer et al. (2017) have observed. Thus, by and large Hypothesis 6 was only partially confirmed.

Nevertheless, the same ANOVA provides further evidence regarding the effect of EVD on attraction effect PR. First, there were significant main effects for decoy types, $F(1, 71)_{\text{choice}} = 83.21$, $p < .001$, partial $\eta^2 = 0.34$; $F(1, 72)_{\text{price}} = 21.91$, $p < .001$, partial $\eta^2 = 0.17$, indicating that the mean contextual PR rates were significantly higher when the decoy $-bets were added than when the decoy P-bets were added, $M_{\text{P-bets/choice}}$ = -32.13%, SD = 73.80%; $M_{\text{\$-bets/choice}}$ = 62.71%, SD = 59.74%; $M_{\text{P-bets/price}}$ = -35.91%, SD = 82.20%; $M_{\text{\$-bets/price}}$ = 36.82%, SD = 84.41%. This is because as opposed to the prediction of the attraction effect that the presence of a decoy P-bet enhances the preference for the target P-bet, the competitor $-bets were significantly more often preferred instead, as evidence by two-sided binomial exact tests (see Appendix G). Second, there was also an enhancement of contextual *choice* PR because the frequencies of the chosen target \$-bets were significantly greater than the frequencies of the chosen competitor \$-bets, $M_\Delta = 30.32\%$, $SE = 3.89\%$, $t(359) = 7.80$, $p < .001$, $d = 0.41$. This pattern was not found for contextual *price* PR, $M_\Delta = 1.01\%$, $SE = 3.87\%$, $t(364) = 0.26$, $p = 0.80$, $d = 0.01$.

Third, the EVD × Decoy Type interaction effects were significant, $F(4, 242)_{\text{choice}} = 16.40$, $p < .001$, partial $\eta^2 = 0.05$; $F(4, 288)_{\text{price}} = 22.01$, $p < .001$, partial $\eta^2 = 0.04$. Post-hoc paired t-tests with Bonferroni corrections reveal that the mean contextual PR rates were significantly truncated (1) from the 50%(↓)- to 50%(↑)-magnitude condition when the decoy P-bets or \$-bets were added within both the choice and price tasks, $M_{\Delta/\text{P-bets/choice}} = 41.67\%$, $SE = 9.23\%$, $t(71) = 4.52$, $p < .001$, $d = 0.53$; $M_{\Delta/\text{P-bets/price}} = 34.25\%$, $SE = 17.97\%$, $t(73) = 4.00$, $p < .001$, $d = 0.38$; $M_{\Delta/\text{\$-bets/choice}} = 27.78\%$, $SE = 12.49\%$, $t(72) = 3.20$, $p = .002$, $d = 0.38$; $M_{\Delta/\text{\$-bets/price}} = 30.14\%$, $SE = 17.83\%$, $t(73) = 3.57$, $p < .001$, $d = 0.41$; and (2) from the 100%(↓)- to 100%(↑)-magnitude condition when the decoy P-bets were added within the price task, $M_\Delta = 68.49\%$, $SE = 10.66\%$, $t(73) = 6.42$, $p < .001$, $d = 0.75$. All the rest pairwise comparisons between the 100%(↓)- and 100%(↑)-magnitude conditions just missed the significance level (all ps $< .100$), and the mean contextual PR rates were all truncated from the former to latter condition (cf., Figure 14).

Taken together, these results indicate that compared with the 50%(↑)- and 100%(↑)-magnitude conditions, the decoy P-bets and \$-bets in the 50%(↓)- and 100%(↓)-magnitude conditions persuaded fewer participants to switch preference from the competitor \$-bets to the target P-bets within both the choice and price tasks. In other words, both the decoy P-bets and \$-bets were not able, on average, to persuade the participants to switch preference from the competitor \$-bets and P-bets with higher EVs to the target P-bets and \$-bets with lower EVs within both the choice and price tasks. In this respect, the effect of EVD is stronger than the attraction effect on the construction of preference.

8.6.1.2 EVL

To further analyze the impact of EVL on contextual PR, we performed simple linear regression analyses. The models explained a statistically significant and very weak proportion of variance and performed significantly better compared to intercept-only base line models, adjusted $R^2_{\text{choice}} = 0.00$, $F(1, 1631)_{\text{choice}} = 12.09$, $p < .001$; adjusted $R^2_{\text{price}} = 0.00$, $F(1, 1627)_{\text{price}} = 7.12$, $p = .008$. More specifically, within the choice task, the final minimal adequate linear regression model was based on 1633 data points and confirmed a significant and positive correlation between the EVLs and the contextual choice PR rates, coefficient estimate = 0.02 (standardized = 0.09, 95% CI [0.04, 0.13]), $SE = 0.01$, $t(1631) = 3.48$, $p < .001$. Within the price task, the final minimal adequate linear regression model was based on 1630 data points and confirmed a significant and positive correlation between the EVLs and the contextual price PR rates, coefficient estimate = 0.01 (standardized = 0.07, 95% CI [0.02, 0.11]), $SE = 0.00$, $t(1627) = 2.67$, $p = .008$. Standardized parameters were obtained by fitting the model on a standardized version of the data set. The 95% CIs and *p*-values were computed using the Wald approximation. These results are consistent with our prediction of Hypothesis 5.

8.6.2. Source discrimination

In order to determine whether there were any recollection biases, one-sample *t*-tests with a test value of zero were computed on the frequencies of recollecting a P-bet or $-bet probe as having been chosen or rejected incorrectly (e.g., choosing the target P-bet but recollecting the decoy P-bet probe as having been chosen). Likewise in Experiment 3: Episodic memory in PR, the data show that all the recollection biases were unanimously significantly biased against zero (see Table 14). Further analyses of paired samples t-tests were computed between the frequencies of recollecting a P-bet or \$-bet probe as having been chosen or rejected correctly and incorrectly. For the P-bets, the participants remembered more correctly that the target, competitor, and distractor P-bets probes were chosen or rejected. However, they did *not* remember more correctly that the decoy P-bets probes were chosen or rejected. The same pattern was also observed for \$-bets. These results indicate that the participants were not simply guessing on the target, competitor, and distractor P-bets and \$-bets probes, but were simply guessing on the decoy P-bets and \$-bets probes.

Table 14: Frequencies of recollection biases: One-sample and paired t-tests.

Bet types	Probe types	Total	M	SD	One-sample t-tests $t(85)$	p	d	Paired t-tests $t(85)$	p	d
P-bets	Targets and competitors	12	3.66	2.23	15.26^{***}	< .001	1.65	9.74^{***}	< .001	1.05
	Decoys	12	5.63	2.13	24.55^{***}	< .001	2.65	1.62	.108	0.18
	Distractors	12	4.94	2.33	19.69^{***}	< .001	2.12	4.22^{***}	< .001	0.46
\$-bets	Targets and competitors	12	3.64	2.07	16.31^{***}	< .001	1.76	10.58^{***}	< .001	1.14
	Decoys	12	6.08	2.06	27.39^{***}	< .001	2.95	-0.37	.715	-0.04
	Distractors	12	5.33	2.42	20.39^{***}	< .001	2.20	2.58^{*}	.012	0.28

* $p < .05$; *** $p < .001$.

8.6.3. Recollection-based responses

To identify retrieval effects on PR, likewise in Experiment 3: Episodic memory in PR, we calculated correct recollection rates as $\frac{\text{hit}}{\text{total response}}$ for each participant. Note that because some total responses are equal to zero for some participants in their respective recollection-based responding, we calculated adjusted rates that correct for this absence as equal to zero. These rates were computed separately for the levels of EVDs, EVLs, age, and gender and for the condition per probe types and PR types. First, for the levels of EVD, a one-way ANOVA test revealed that the mean correct recollection rates were *not* significantly different across all the EVDs, $F(4,\ 340) = 0.26$, $p = .903$; $M_{0\%} = 68.61\%$, $SE = 2.06\%$; $M_{50\%(\downarrow)} = 71.80\%$, $SE = 2.86\%$; $M_{50\%(\uparrow)} = 70.35\%$, $SE = 2.66\%$; $M_{100\%(\downarrow)} = 70.64\%$, $SE = 2.59\%$; $M_{100\%(\uparrow)} = 70.06\%$, $SE = 2.74\%$.

Second, for the levels of EVL (median split), a paired t-test revealed that the mean correct recollection rates were *not* significantly different between the low and high EVLs, $t(85) = 0.67$, $p = .502$, $d = 0.07$; $M_{\text{Low (EV} \leqslant \text{16 PLN)}} = 70.57\%$, $SE = 1.89\%$; $M_{\text{High (EV} > \text{16 PLN)}} = 69.35\%$, $SE = 1.78\%$. Third, for the levels of age (median split), an unpaired two-sample t-test revealed that the mean correct recollection rates were *not* significantly different between the young and old participants, $t(84) = 0.36$, $p = .724$, $d = 0.05$; $M_{\Delta} = 1.15\%$, $SE = 3.44\%$. Fourth, for the levels of gender, an unpaired two-sample t-test revealed that the mean correct recollection rates were *not* significantly different between the female and male participants, $t(84) = 0.76$, $p = .450$, $d = 0.11$; $M_{\Delta} = 2.43\%$, $SE = 3.22\%$. Taken together, these results indicate that either the EVDs, EVLs, age, or gender did not have an effect on the participants' correct recollections.

Fifth, for the condition per probe types and PR types, Table 15 shows the descriptive findings of the mean correct recollection rates (cf., Figure 15). A 2 (probe type: targets and competitors vs. decoys) × 4 (PR type: predicted vs. unpredicted vs. equivalent vs. non-PR) repeated-measures ANOVA on the mean correct recollection rates showed that there were significant main effects, $F(1, 85)_{\text{probe type}} = 139.72$, $p < .001$, partial $\eta^2 = 0.19$; $F(3, 255)_{\text{PR type}} = 25.74$, $p < .001$, partial $\eta^2 = 0.11$. Post-hoc paired t-tests with Bonferroni corrections reveal that, for the targets and competitors, the mean correct recollection rates significantly increased (1) for non-PR than predicted PR, $M_\Delta = 16.74\%$, $SE = 5.14\%$, $t(85) = 3.26$, $p = .002$, $d = 0.35$; and (2) for non-PR than unpredicted PR, $M_\Delta = 27.30\%$, $SE = 5.04\%$, $t(85) = 5.42$, $p < .001$, $d = 0.58$.

Table 15: Mean correct recollection rates per probe types and PR types.

Probe types	PR types	M (%)	SD (%)
Targets & competitors	Predicted	53.14	40.38
	Unpredicted	42.58	41.28
	Equivalent	42.24	44.86
	Non-PR	69.88	18.84
Decoys	Predicted	16.94	34.78
	Unpredicted	10.27	29.28
	Equivalent	4.65	21.18
	Non-PR	39.51	44.65

The same pattern was also observed for the decoys, such that the mean correct recollection rates significantly increased (1) for non-PR than predicted PR, $M_\Delta = 22.57\%$, $SE = 5.93\%$, $t(85) = 3.81$, $p < .001$, $d = 0.41$; and (2) for non-PR than unpredicted PR, $M_\Delta = 29.24\%$,

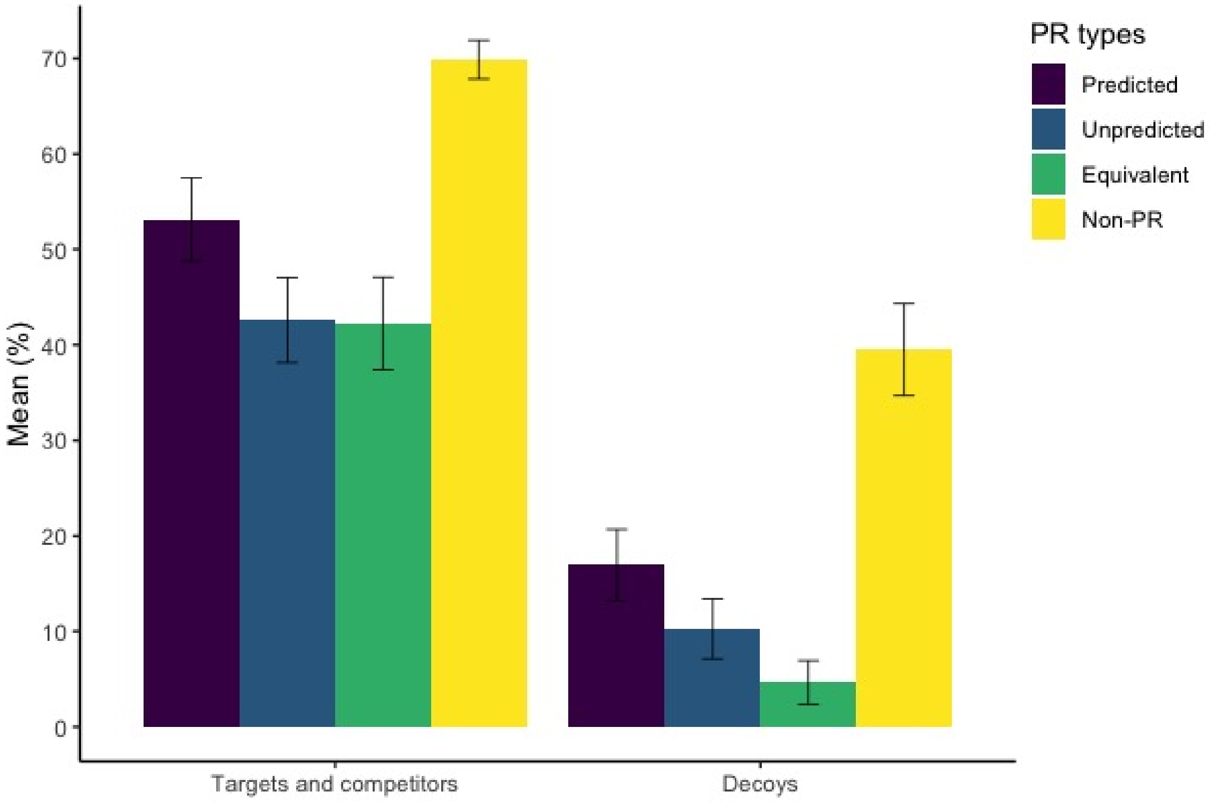


Figure 15: Mean correct recollection rates per probe types and PR types.
Note: Error bars are the ±1 standard error of the mean.

$SE = 5.63\%$, $t(85) = 5.20$, $p < .001$, $d = 0.56$. The Probe Type × PR Type interaction effect was not significant, $F(3, 255) = 0.41$, $p = .744$, partial $\eta^2 = 0.00$. (For the analyses on the condition per EVDs and PR types and on the condition per EVLs and PR types, see Appendix H.) Taken together, these results indicate the involvement of episodic memory in attraction effect PR, such that people seem likely to recollect bets more correctly when they exhibit a consistent preference than when they exhibit predicted or unpredicted PR. Thus, once again, Hypothesis 7 was confirmed.

8.7. Discussion

It appears likely that the lack of a steady reduction effect of EVD in the findings of attraction effect PR was due to three reasons. First, when comparing binary differences of predicted classifications (${\eta_p}^2 = 0.02$), a conservative (i.e., the smallest) decision number of

144 in each classification would be necessary for a power of 0.80 when conducting a two-tailed test ($p = .05$) to detect statistically significant differences in all pairwise comparisons (Faul, Erdfelder, Buchner and Lang, 2009). The present experiment implemented a rather small extent of stimulus magnitude to make our participants less fatigued, and consequently, the statistical power of hypothesis testing on the anticipated effect size may be not sufficiently large to detect a difference in preferences in certain conditions.

Second, we modeled our stimuli using a gain-loss design, which is different from the original gain-zero design and in various other aspects of Farmer et al. (2017), such as the magnitudes of probability, payoff, and EVD, the conditions of time control, and the incentives mechanisms. Thus, we believe that the other reason for the discrepancy is that it is still unclear whether this reduction effect is still sustainable in the current context of the PR design. Third, it has been argued that contextual PR, including the attraction, compromise, similarity, and phantom effects, is not a violation of the axioms of rationality; rather, it is a computationally bounded consequence of EV maximization given noisy observations by perceptual and cognitive constraints (Howes et al., 2016). Our analysis confirms this finding in that the extent to which our participants maximized EVs more greatly suppressed or enhanced the proportion of preference than that the attraction effect arose.

There may be two reasons that the current results failed to replicate the attraction effect when inferior decoy P-bets were added. First, some studies were unsuccessful in accommodating the attraction effect when choice options were presented in a pictorial rather than abstract numerical form (Frederick et al., 2014; Yang and Lynn, 2014). This is because the former form make the superiority versus inferiority relationship between the target and the decoy less salient than the latter form. At the same time, a fast and unambiguous ability to identify the dominance relationship is a critical condition for obtaining the attraction effect. Since we also implemented the bet stimuli in a pictorial form, such a failure may also happen in our manipulation.

Second, according to the multialternative decision field theory, the preference for the target is reduced via a “similarity effect” when the decoy is very similar, albeit not clearly inferior, to the target (Roe, Busemeyer and Townsend, 2001). In our experiment, the decoys were also not clearly inferior to the targets in that although they only differed in the probability grid, the position of the green squares within the grid was randomized, which made it somewhat difficult to compare the quantities of the green squares. Although the context-dependent model predicts maximal attraction effects when closer decoys are present (Tversky and Simonson, 1993), it is intuitively doubtful whether those decoys can powerfully modulate the preference for the close targets, as they might be barely distinguishable. Critically, our participants showed, on average, a remarkably stronger preference for the target or competitor $-bet (see Appendix G). Then, the transfer of attention toward an undesirable P-bet and then an ultimate choice reversal require that the decoy is more strongly inferior but less similar to the target, as evidenced by more recent eye-tracking and neuroscience studies (e.g., Alós-Ferrer and Ritschel, 2022; Król and Król, 2019; Mohr, Heekeren and Rieskamp, 2017).

The data also show that the correct recollection rates of the four PR types (i.e., predicted, unpredicted, equivalent, non-PR) for the targets and competitors were much higher than the corresponding rates for the decoys. The reason can be explained by the results from the source discrimination that the participants were not simply guessing on the target and competitor probes but were simply guessing on the decoy probes. Then, it was the targets and competitors that the participants remembered better because they attracted more evaluative processing. That is, gist representations were likely involved for the decoys in both choice and price judgments, whereas fine-grained verbatim processing may tap more precise representations for the targets and competitors. Thus, it was not surprising that the targets and competitors yielded the better recollection rates than the decoys in the memory test. We also argue that if we could endow our participants with perfect memory, then we could make some of PR that was caused by the recollection bias disappear, given that the correlation between false episodic memory and limited preference sensitivity may actually have a causal relationship.

9. Binary choice and PR: Three meta-analyses

Insights into how PR is revealed can help academics better understand the processes and factors involved with how choice preferences are constructed, and how they are affected by their relative payoffs. From an applied perspective, gamblers face a multiple number of betting offers to choose from in today's gambling markets. Practitioners like dealers and gambling policy advocates would need to re-think their practice of providing an assortment of product portfolio, since they could possibly boost their success by predicting customer preferences for specific gambles. Given these implications, it is important to learn how robust choice preferences and predicted and unpredicted PR are, and to what extent they occur in different situations.

To synthesize the available findings, we conducted three meta-analyses across all experiments either published in refereed journals or unpublished that we are aware of that investigated the influence of payoff magnitude on binary choice and predicted and unpredicted PR. To the best of our knowledge, until now no meta-analysis pertaining to the PR phenomenon has been conducted to integrate results of these studies. In the end, it is hoped to distill, from a relative payoff magnitude perspective, the sufficient conditions to create PR so that researchers can design more effective and extensible experiments to more systematically test for the sources and moderators of PR.

9.1. Method

9.1.1. Study retrieval

We searched the electronic databases PsycArticles, PsycInfo, EBSCO, and ProQuest Dissertations & Theses Global using the term "preference reversal" in the title, in which the EBSCO searches were narrowed to include only "Peer Reviewed" journals. The identified papers were published between 1913 (first published study) and 2022. We also conducted an additional search using the reference lists of the identified papers and Google Scholar. Both searches were conducted by August 25, 2022, and we initially secured 2,650 studies from the three databases and 716,000+ results from Google Scholar. We first read titles and abstracts for applicability to PR. When a reading of the abstract did not readily reveal applicability, we read the full article to determinate its relevance to PR. Manual reference list and Google Scholar did not result in articles that were not already identified through the database search.

9.1.2. Inclusion criteria

The meta-analytic integration of different studies requires that designs and research questions are compatible. Therefore, we only included data from experiments in which participants were given a series of hypothetical or real binary choice, rather than other elicitation methods (e.g., rankings, attractiveness ratings), as a dependent measure to compare with minimum selling or maximum buying prices, with the participants being subject to experimental manipulation in a within-subjects design. Given our focus on identifying magnitude effects on PR, we sought out studies that (1) included a loss or gain ratio as an independent variable; and (2) the dependent variable was either a measure of propensity to make a choice between a safe bet and a risky bet, or a measure of propensity to reveal predicted and unpredicted PR.

First, the majority of the studies were excluded due to the following reasons: (1) no choice and price tasks used, (2) no experiment involved, (3) no loss or gain ratio of the stimuli revealed, (4) low and high loss or gain ratios pooled over bet pairs, (5) data not available for consistent and inconsistent frequencies, (6) data not available for predicted and unpredicted PR frequencies, (7) measures related to intertemporal choices and preferences, (8) duplicate references, (9) non-human beings as subjects, or (10) no independent variables of relevance to the meta-analyses. To our surprise, only a total of 27 studies among the ocean of literature satisfied our criteria, which echo pure replications of the classic Lichtenstein and Slovic's (1971) study. No unpublished experiments and dissertations were included.

It should be noted that (1) the gain-zero or gain-loss design is the best-known and most frequently studied format in a PR experiment; (2) a few experiments—especially earlier ones—used small losses instead of zero payoffs; and (3) the loss-zero design was not typically implemented in the literature. However, those past studies often lack for bet pairs with high loss or gain ratios as compared to those prevailing ones with low loss or gain ratios, given that -5.0 in the gain-loss design or 10.0 in the gain-zero design is assumed as a threshold ratio for low versus high loss or gain ratios, respectively (cf., Figure 1). The threshold of loss ratio -5.0 was adapted on the basis of a rough mean between the low and high loss threshold ratios -2.5 and -8.0, respectively, that is, -5.0 $\approx \frac{-2.5 + (-8.0)}{2}$, according to the results in Experiment 1: Magnitude effects in PR. The gain threshold ratio 10.0 was adapted on the basis of prospect theory, which suggests that losses loom about twice larger than gains (Kahneman and Tversky, 1979). That is, a low loss or gain ratio is presumably no more than -5.0 or 10.0, respectively, whereas a high loss or gain ratio is presumably equal to or no less than -5.0 or 10.0, respectively.

Then, we only included studies that consisted of bet pairs with both the above low and high loss or gain ratios. Our units of analysis were the individual scenarios of the experiments or treatments reported in the relevant studies. For example, an experiment featuring 5 lottery pairs yielded 5 meta-analytic scenarios. Thus, in total, the current meta-analyses include data from 125 scenarios derived from 12 experiments or treatments across 7 studies, including

6 published journal articles and Experiment 3: Episodic memory in PR, and embraced a total of 884 valid participants. Less studies would be included if the threshold of loss or gain ratio becomes smaller or larger than -5.0 or 10.0, respectively. A single article (experiment or treatment) that included multiple experiments or treatments (scenarios) may have one, a portion of, or all its experiments or treatments (scenarios) included in the meta-analyses. The scenarios were assigned to reflect one of the two independent variables.

A summary of the experimental data of the 7 studies included in the meta-analyses is given in Table 16, which outlines the underlying studies, experiments or treatments, moderators, total sample and mean sizes, and effect sizes. The rest 20 studies got no weight in the combined effects due to a lack of bet pairs with either low or high loss or gain ratios to derive quantitative choice or PR shares for either control or experimental condition. A detailed overview of the individual scenarios and experiments of all the 27 studies can be found online at https://doi.org/10.1037/npe0000145.supp. (Most of these data were not given in the original articles, but could be reconstructed from the reported marginal frequencies.)

9.2. Statistical methods

9.2.1. Common and random effects models

We integrated the results of all data by calculating common effect models and random effects models (Borenstein, Hedges, Higgins and Rothstein, 2010), both without and with missing data due to dropouts of responses with tied preferences. The former models assume that there is one true effect size which is shared by all the included studies. By contrast, the latter models assume that the effect sizes for each study are randomly distributed around a grand mean effect size. The outcome of interest is an increase of frequency of safe bet choice, predicted, or unpredicted PR, and the chosen measure of association is the risk ratio

Table 16: Overview of all data included in the meta-analyses.

Author/article	Experiment or treatment[a]	ID	Total sample size	Moderators: PR design[b]	Moderators: Evaluation mode	Scenario size	Ratio level	Safe bet choice: M size	Safe bet choice: Effect size d	Safe bet choice: Effect size Variance	Predicted PR: M size	Predicted PR: Effect size d	Predicted PR: Effect size Variance	Unpredicted PR: M size	Unpredicted PR: Effect size d	Unpredicted PR: Effect size Variance
Ball et al. (2012). "Do preference reversals generalise? Results on ambiguity and loss aversion."	1	1	52	+ 0	Separate	5	Low	35.8	-0.33	0.02	17.8	-0.09	0.02	4.6	0.04	0.02
						1	High	43.0			20.0			4.0		
	2	2	52	+ 0	Separate	5	Low	33.6	-0.58	0.02	17.0	0.04	0.02	5.8	0.68	0.02
						1	High	46.0			16.0			0.0		
Chai (2005). "Cognitive preference reversal or market price reversal?."	1	3	186	+ 0	Separate	8	Low	94.0	0.46	0.01	29.8	0.03	0.01	21.5	-0.07	0.01
						4	High	53.0			27.8			25.8		
Guo (2021). "Contextual deliberation and the choice-valuation preference reversal."	1	4	59	+ 0	Separate	12	Low	25.1	-0.54	0.02	21.1	-0.30	0.02	2.6	0.13	0.02
						6	High	40.8			29.7			1.3		
	2	5	59	+ 0	Joint	12	Low	27.0	-0.36	0.02	11.9	-0.09	0.02	3.3	-0.05	0.02
						6	High	37.5			14.0			4.0		
Lu (2022). "Experiment 3: Episodic memory in PR."	1	6	64	+ -	Separate	8	Low	22.9	-0.42	0.02	12.4	-0.33	0.02	9.6	0.18	0.02
						8	High	36.2			21.6			5.8		
Lu and Nieznański (2021). "Magnitude effects in preference reversals."	1	7	39	+ -	Joint	1	Low	19.0	-0.20	0.03	15.0	-0.17	0.03	2.0	0.28	0.03
						6	High	22.8			18.2			0.3		
	1	8	57	+ -	Joint	1	Low	49.0	0.43	0.02	24.0	0.22	0.02	3.0	0.09	0.02
						2	High	39.0			18.0			2.0		
	2	9	113	+ -	Joint	23	Low	69.0	-0.04	0.01	N/A	N/A	N/A	N/A	N/A	N/A
						3	High	71.3			N/A			N/A		
Mowen and Gentry (1980). "Investigation of the preference reversal phenomenon in a new product introduction task."	1	10	32	+ -	Joint	4	Low	22.0	-0.37	0.03	10.8	0.27	0.03	2.0	0	0.03
						1	High	27.0			7.0			2.0		
	2	11	65	+ -	Joint	4	Low	48.8	0.30	0.02	34.3	1.15	0.02	2.7	-0.82	0.02
						1	High	39.7			3.6			21.7		
Zhang (1999). "An experimental study on risky features of alternatives and preference reversal."	1	12	124	+ 0	Joint	2	Low	49.5	-0.03	0.01	32.0	-0.07	0.01	14.0	0.05	0.01
						1	High	51.0			36.0			12.0		

[a] *Experiment or treatment* indicates the number of the experiment or treatment in the corresponding study.
[b] *Key*: + 0 = Gain-zero design; + - = Gain-loss design (see Table 2).

(RR), with an RR larger than 1 meaning that the frequency of safe bet choice, predicted, or unpredicted PR of bet pairs with low loss or gain ratios is larger than that with high loss or gain ratios. The common and random effects models were run with the method by Paule and Mandel (Jackson, Veroniki, Law, Tricco and Baker, 2017) as implemented by the `meta` package in R 4.2.1.

9.2.2. Three-level meta-regression models

Two potential sources of misspecification is that multiple scenarios of safe bet choice, predicted, or unpredicted PR may come from a single experiment, and multiple experiments or treatments may have been sourced from a single study. The current data set includes several instances where multiple scenarios were extracted from a single "parent" study (12 experiments or treatments derived from 7 studies). Given the nested nature of the data, combining multiple dependent variables from a single study violates the statistical assumption of independence of observations because inter-study observations may be correlated to one another. Thus, to check for possible within-study correlations, we also fit the data to three-level meta-regression models, in which two levels capture the specific effect sizes across studies and a third level captures the underlying studies.

To integrate the individual studies into a format suitable for three-level meta-regression models, we transformed the differences of safe bet choice and of predicted and unpredicted PR rate between bet pairs with low and high loss or gain ratios within individual studies into effect size measures represented by Cohen's d—an approach commonly used in meta-analysis (Cohen, 1988). Since the decision outcomes are measured on a binary scale, the magnitude of Cohen's d is measured from raw data in the manuscripts using the arcsine transformation (Chernev, Böckenholt and Goodman, 2015; Lin and Xu, 2020), that is, $d =$

$2 \times \text{arcsine}\sqrt{\frac{M_{\text{low}}}{n}}$ - $2 \times \text{arcsine}\sqrt{\frac{M_{\text{high}}}{n}}$, where M_{low} and M_{high} represent the mean sizes of participants among a total sample size n who make a choice or reveal a type of PR for bet pairs from each ratio level. A positive or negative d indicates the presence or refusal of favoring a safe bet, respectively. The variance for an effect size d is $\frac{1}{n} + \frac{d^2}{2n(n-1)}$, where n is the sample size of a study (Koenig, Eagly, Mitchell and Ristikari, 2011). The three-level meta-regression models were run with the restricted maximum likelihood approach as implemented by the `metafor` package in R 4.2.1 (Vevea and Coburn, 2015).

9.2.3. Robust variance estimation and cluster wild bootstrapping

We also fitted correlated and hierarchical effects models with robust variance estimation to guard our three-level meta-regression models against potential misspecification (Moeyaert, Ugille, Beretvas, Ferron, Bunuan and Van den Noortgate, 2016). To avoid inflated Type I error rates when the number of studies is small, we used the cluster wild bootstrapping approach to conduct hypothesis tests (Joshi, Pustejovsky and Beretvas, 2022). These methods are implemented by the `clubSandwich` and `wildmeta` packages in R 4.2.1.

9.3. Results

9.3.1. Safe bet choice

The forest plot for the common and random effects models as well as the subgroup analyses by presence of missing data in the studies are shown in Figure 16. For the random effects model, the mean effect of frequency of safe bet choice across all the studies was RR = 0.97 (95% CI [0.78, 1.20]). The between-study variance equaled $\tau^2 = 0.08$. The I^2 statistic that quantifies the proportion of variance due to non-random heterogeneity equaled 83% (CI [68%, 91%]), which indicates high heterogeneity. The diamonds presenting the estimated RRs and confidence limits as well as the prediction interval crossed the line of no effect, suggesting that there are no significant differences between bet pairs with low and high loss or gain ratios in choosing safe bets.

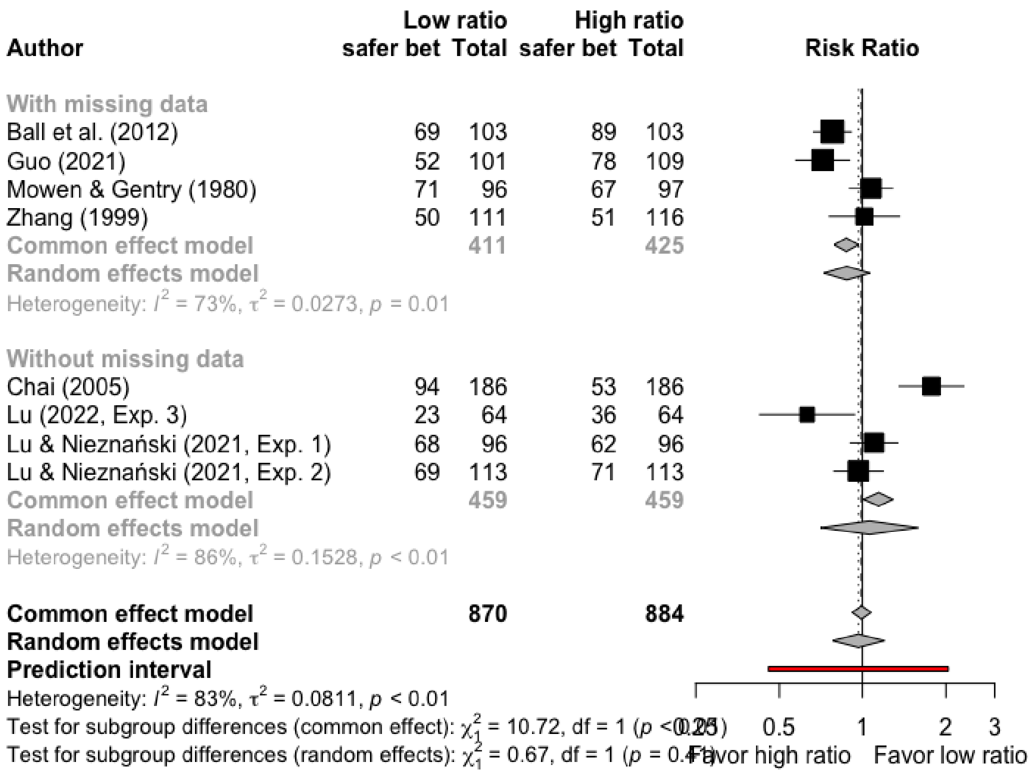


Figure 16: Forest plot of binary choice.
Note: Lu (2022, Exp. 3) = Experiment 3: Episodic memory in PR.

As expected, the CI for the summary estimate from the random effects model was wider compared with the one from the common effect model, but the two results differed only slightly in terms of magnitude. Studies without missing data reported a larger effect of safe bet choice compared with those with missing data. All CIs for the subgroup estimates included or slightly missed the respective overall effect. The test for subgroup differences under the *common effect* model displayed in the forest plot supported the visual detection, suggesting that missing data might have some impact on the results (p = .001). However, the test for subgroup differences under the *random effects* model did not differ significantly (p = .413), with RRs ranging from 0.92 to 1.02 for the extreme worst and best case scenarios under several imputation methods such as Gamble-Hollis (Gamble and Hollis, 2005). This suggests that missing data did not have a serious impact on the data set under the random effects model.

The funnel plots are shown in Figure 17. The common effect model is represented by a dashed line on which the funnel is centred, while the random effects model estimate is indicated by a dotted line (Panel A). Both estimates are similar; they cannot be well distinguished. The funnel plot looks relatively symmetric about the mean, which implies that the estimated RRs were relatively normally distributed, with few missing "file-drawer" studies. Moreover, based on the contour-enhanced funnel plot (Panel B), publication bias seemed not to be the dominant factor as most small studies with large SEs lied in the white area corresponding to non-significant ratio-level estimates. The Harbord test was not significant (p = .730), supporting the absence of small-study effects. The trim-and-fill method added no study to the data set (Panel C). The result of the limit meta-analysis indicates the adjusted estimate RR = 1.06 (95% CI [0.70, 1.62]), covering the line of no effect (Panel D).

The three-level meta-regression model yielded an estimate of pooled effect size d = -0.12 (95% CI [-0.37, 0.13]). The resultant t-statistic indicated a statistically non-significant association between safe bet choice and any loss or gain ratio levels, $t(11)$ = -1.08, p = .304. Compared to a two-level model, such as the common effect or random effects model, with level 3 heterogeneity constrained to zero, however, the three-level model showed a worse fit, according to a likelihood ratio test comparing both models, $\chi^2(1) = 0.14$, p = .715. From this standpoint, the meta-regression conducted did not actively seek to correct for autocorrelation within studies. Moreover, a subgroup analysis indicated that effect sizes did not differ depending on the PR design (gain-zero or gain-loss) as a moderator, $F(1, 10) = 0.54$, p = .481.

A correlated and hierarchical effects model with robust variance estimation yielded an

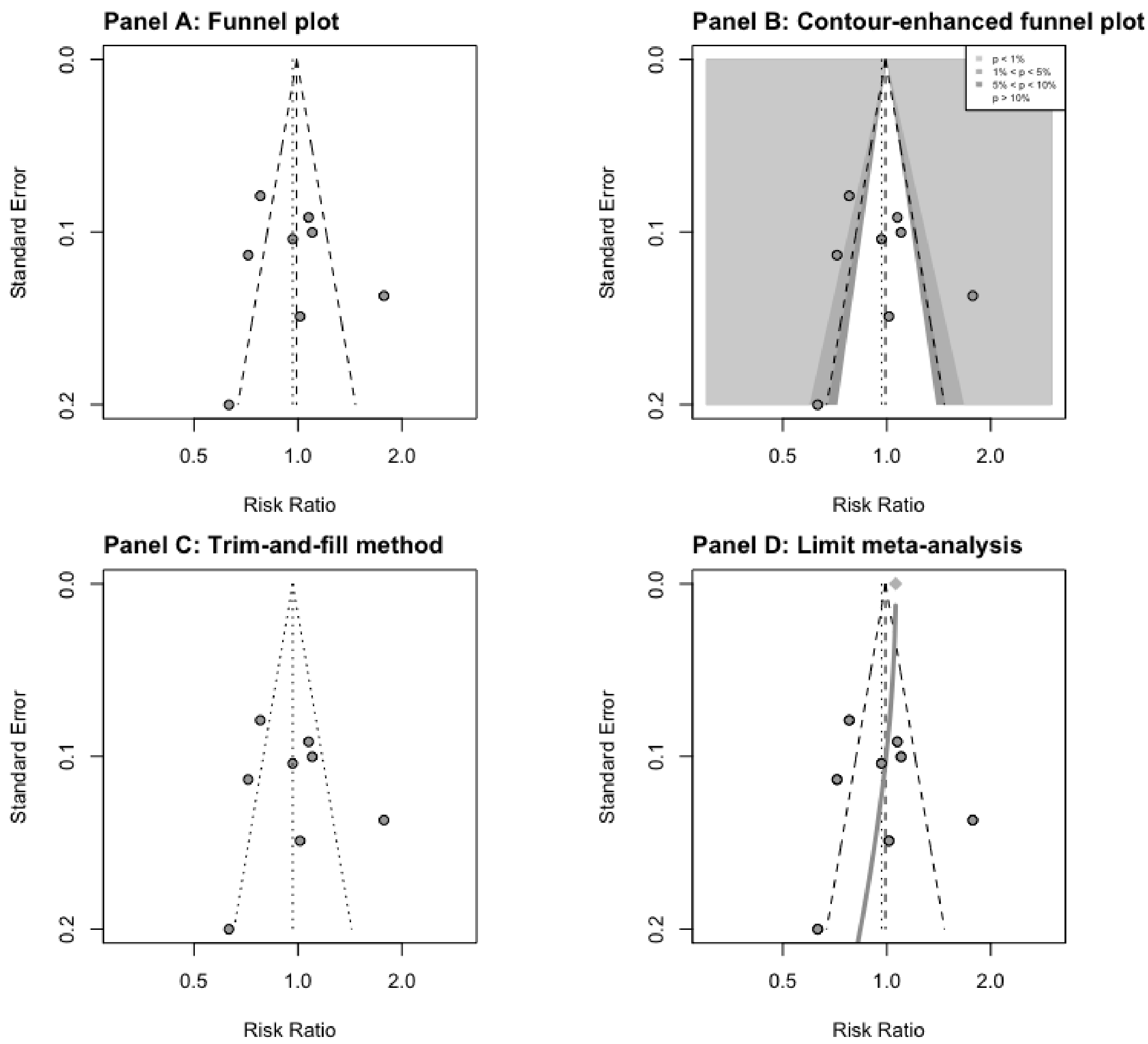


Figure 17: Funnel plots of binary choice.

estimate similar to the one obtained above, d = -0.05 (95% CI [-0.38, 0.28]), and none of the coefficients were significant, t = -0.50, p = .657. Similar to the finding of the three-level meta-regression model, a moderator test of the PR design with the cluster wild bootstrapping approach was not significant, p = .625.

9.3.2. Predicted and unpredicted PR

The forest plots for the common and random effects models as well as the subgroup analyses by presence of missing data in the studies are shown in Figure 18 and Figure 19.

For the random effects model, the mean effects of frequency of predicted and unpredicted PR across all the studies were $RR_{predicted} = 1.09$ (95% CI [0.70, 1.71]) and $RR_{unpredicted} = 1.06$ (95% CI [0.57, 1.97]), respectively. The between-study variances equaled $\tau^2_{predicted} = 0.31$ and $\tau^2_{unpredicted} = 0.45$. The heterogeneity statistics equaled $I^2_{predicted} = 78\%$ (CI [54%, 89%]) and $I^2_{unpredicted} = 64\%$ (CI [19%, 84%]), which indicate high heterogeneity. The diamonds presenting the estimated RRs and confidence limits as well as the prediction interval crossed the line of no effect, suggesting that there are no significant differences between bet pairs with low and high loss or gain ratios in revealing predicted and unpredicted PR.

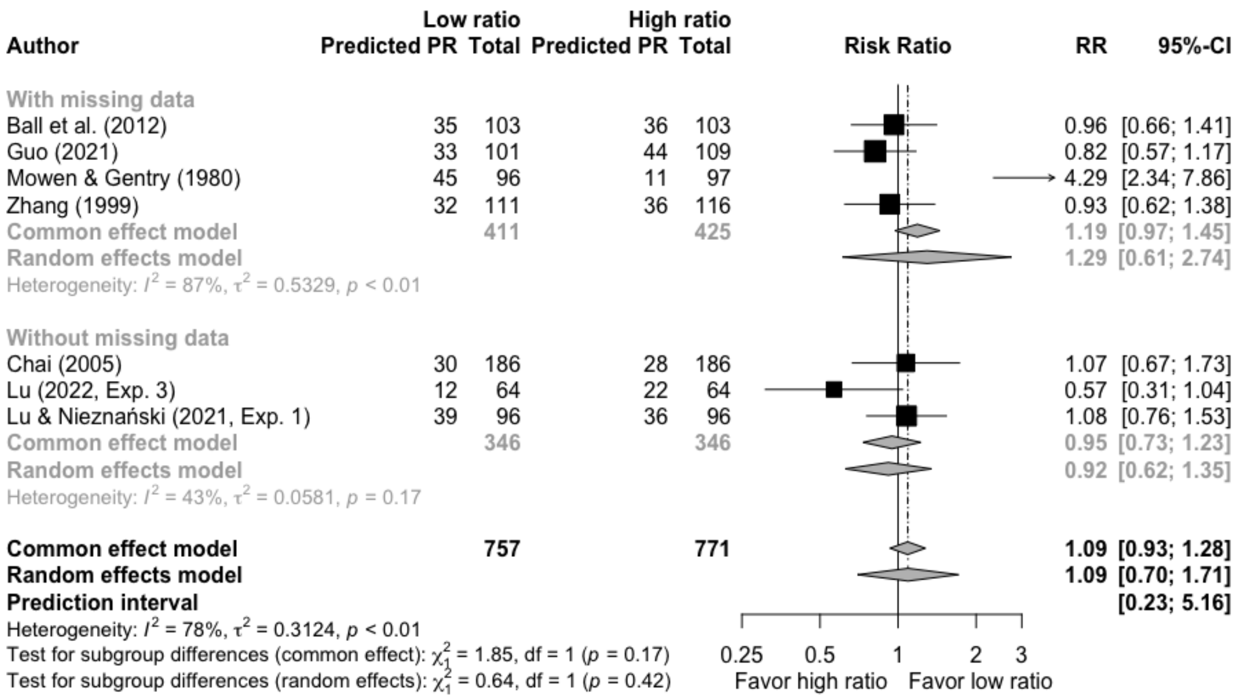


Figure 18: Forest plot of predicted PR.

As expected, the CI for the summary estimate from the random effects model was wider compared with the one from the common effect model, but the two results differed only slightly in terms of magnitude. Studies without missing data reported slightly smaller or larger effects of predicted and unpredicted PR compared with those with missing data. The test for subgroup differences under both the models did not differ significantly (all $ps > .150$),

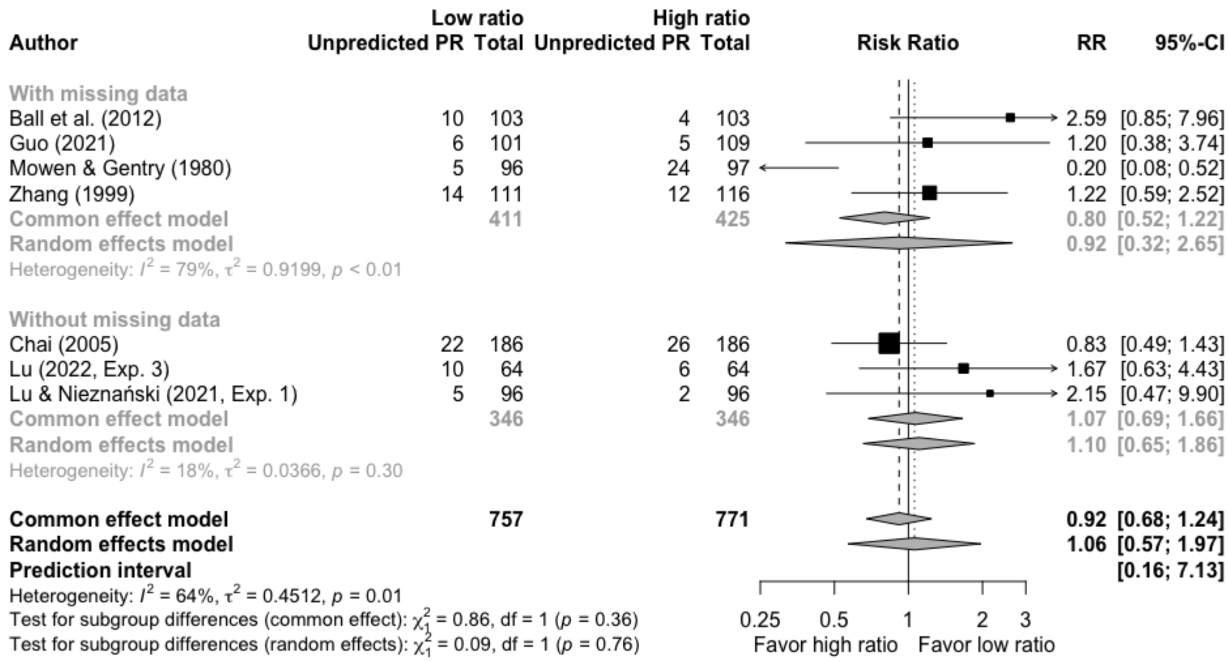


Figure 19: Forest plot of unpredicted PR.

with RRs ranging from 1.07 to 1.20 for predicted PR and from 0.95 to 1.02 for unpredicted PR for the extreme worst and best case scenarios under several imputation methods. This suggests that missing data did not have a serious impact on the data set under both the models.

The funnel plots of predicted and unpredicted PR are shown in Figure 20 and Figure 21, respectively. The estimates of both the models are similar; they cannot be well distinguished (Panel A). The funnel plots clearly look relatively asymmetric (Panel B); however, based on the contour-enhanced funnel plots (Panel B) and non-significant results of the Harbord test (all ps $>$ .200), the data set seemed to be absent from small-study effects. The trim-and-fill method added no studies for predicted PR to the data set, but added the two studies (Ball et al., 2012; Lu and Nieznański, 2021, Experiment 1: Magnitude effects in PR) with the lowest effect sizes for unpredicted PR (Panel C), leading to an adjusted random effects estimate $\text{RR}_{\text{unpredicted}} = 0.84$ (95% CI [0.46, 1.52]) while an unchanged variance $I^2{}_{\text{unpredicted}}$

= 64%. This indicates that the difference of the heterogeneity in the data set was due to the filled studies reporting large effect sizes. The result of the limit meta-analyses indicates the adjusted estimates $RR_{predicted}$ = 0.62 (95% CI [0.16, 2.32]) and $RR_{unpredicted}$ = 0.91 (95% CI [0.37, 2.24]), both covering the line of no effect (Panel D).

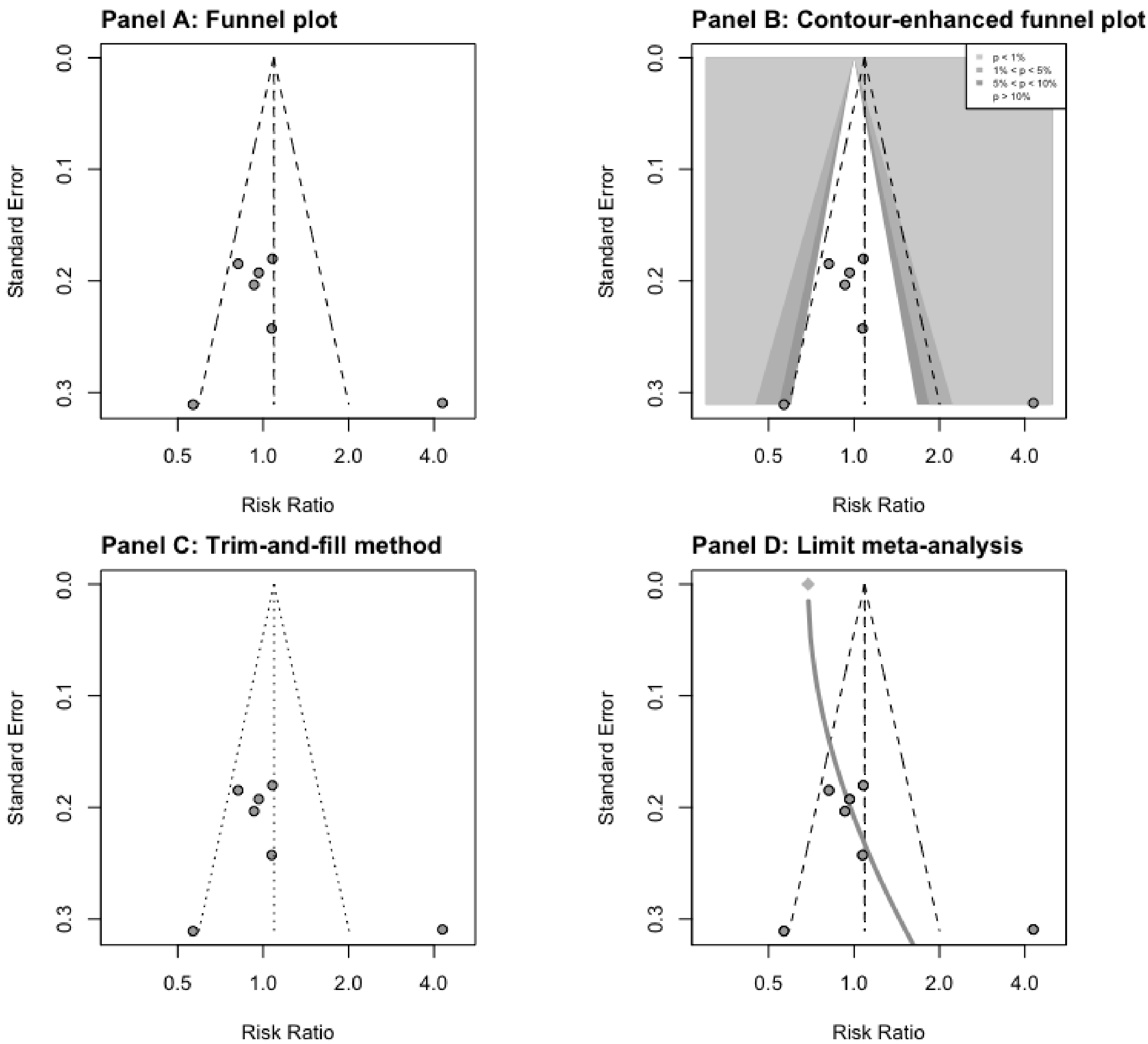


Figure 20: Funnel plots of predicted PR.

The three-level meta-regression models yielded estimates of pooled effect size $d_{predicted}$ = 0.05 (95% CI [-0.26, 0.35]) and $d_{unpredicted}$ = 0.04 (95% CI [-0.21, 0.29]). The resultant t-statistics indicated statistically non-significant associations between both predicted and unpredicted PR and any loss or gain ratio levels, $t(10)_{predicted} = 0.34$, $p = .739$; $t(10)_{unpredicted}$

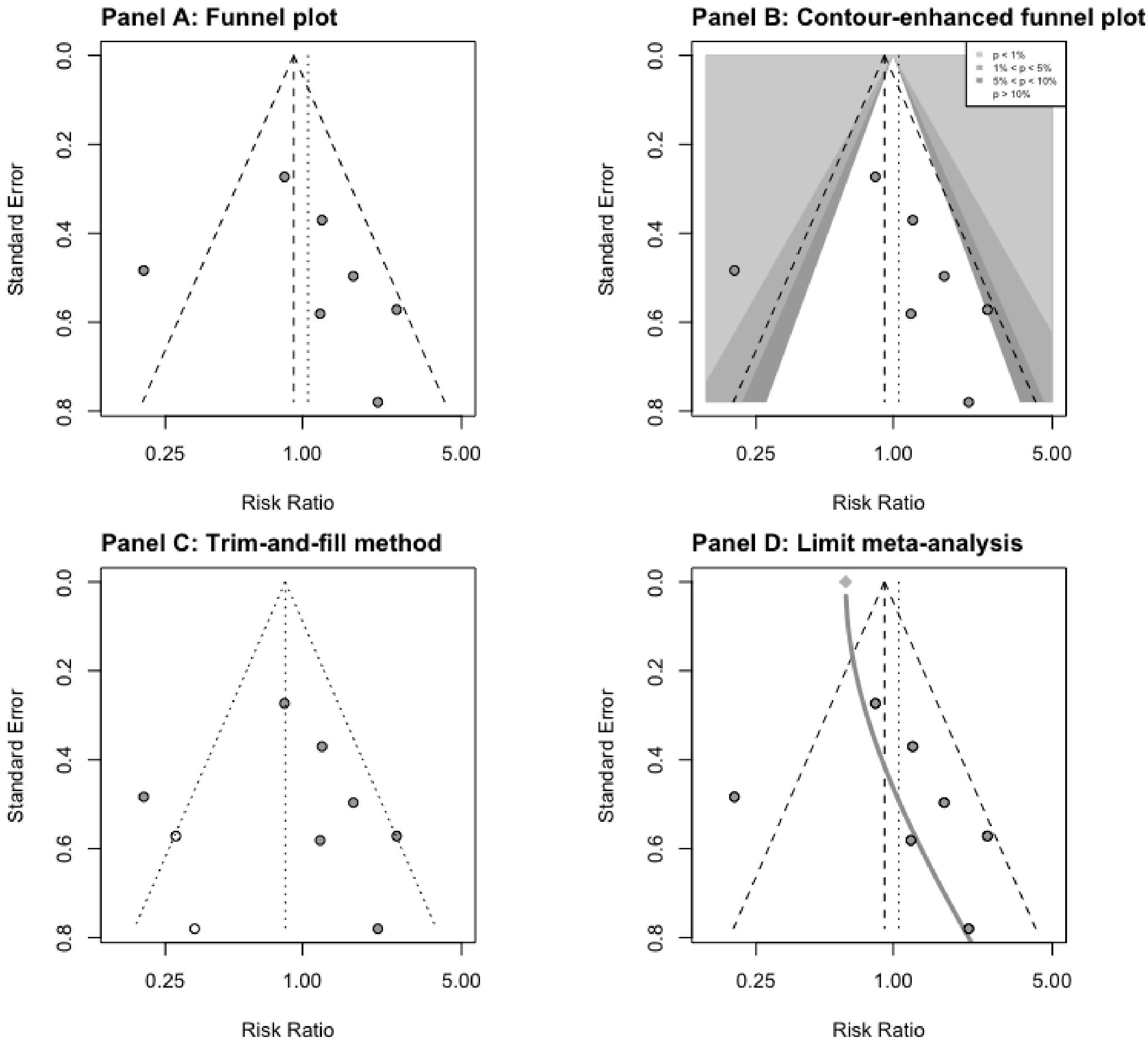


Figure 21: Funnel plots of unpredicted PR.

= 0.38, p = .713. Compared to a two-level model, however, the three-level model showed a worse fit according to likelihood ratio tests comparing both models, $\chi^2(1)_{\text{predicted}} = 0.65$, p = .421; $\chi^2(1)_{\text{unpredicted}} = 0.07$, p = .793. Moreover, subgroup analyses indicated that effect sizes do not differ depending on either (1) the PR design (gain-zero or gain-loss) as one moderator, $F(1,\ 9)_{\text{predicted}} = 1.10$, p = .322; $F(1,\ 9)_{\text{unpredicted}} = 0.62$, p = .451; or (2) the evaluation mode (separate or joint) as another moderator, $F(1,\ 9)_{\text{predicted}} = 0.49$, p = .503; $F(1,\ 9)_{\text{unpredicted}} = 1.05$, p = .333.

Correlated and hierarchical effects models with robust variance estimation yielded estimates similar to the ones obtained above, $d_{\text{predicted}} = 0.21$ (95% CI [-1.16, 1.57]); $d_{\text{unpredicted}} = -0.06$ (95% CI [-1.11, 1.00]), and none of the coefficients were significant, $t_{\text{predicted}} = 0.68$, $p = .569$; $t_{\text{unpredicted}} = -0.25$, $p = .828$. Similar to the findings of the three-level meta-regression models, moderator tests of both the PR design and evaluation mode with the cluster wild bootstrapping approach were not significant, all ps > .300.

9.4. Discussion

The purpose of this study was to systematically analyze the conditions under which safe bet choice and predicted and unpredicted PR have been observed. Findings from a series of two- and three-level models indicated that there seem to be no effects of low versus high loss or gain ratios. Thus, the findings of the current meta-analyses and Experiment 1: Magnitude effects in PR as well as Experiment 3: Episodic memory in PR were not convergent in their conclusions. The results also suggested no indications that the PR design (gain-zero or gain-loss) or the evaluation mode (separate or joint) is associated with the shares of safe bet choice and predicted and unpredicted PR. While some factors may cause non-significant effects, including differences in study targets, experimental methods, timing of outcome measurements, interventions, and/or stimuli, we reason three explanations for the conflicting results in the above studies.

First and foremost, the thresholds that divided loss and gain ratios into low and high conditions at the level of the current meta-analytic data are -5.0 and 10.0, respectively, which are larger than the low condition, no more than -2.5 and 5.1, but are smaller than the high condition, no less than -6.0 and 17.9, at the level of the data of Experiment 1: Magnitude effects in PR and Experiment 3: Episodic memory in PR, respectively. Then, near half of low and high loss or gain ratios between -2.5 and -6.0 or between 5.1 and 17.9, respectively (55 out of 125 scenarios), are seemingly at turning points of unstable preference from choosing safe to risky bets. That being said, we implemented these thresholds for the sake that as many studies as possible could be included in the meta-analyses; otherwise, available data would be insufficient to conduct an analysis of either low or high ratio condition. The incongruous presumptions about low and high loss or gain ratios may lead to the discordant conclusions. Finding reliable, externally valid conditions and moderators of PR will require a variety of scenarios, so future researchers should use substantially small and large ratios when studying this phenomenon.

Second, the number of studies may have been considered to be too small for the meta-analyses. Many studies were excluded because either scenarios were absent from low or high loss or gain ratios at the level of the meta-analytic data, or scenario-level choice and PR shares and stimulus could not be disaggregated from the reported data. As a result, the lack of ratio- and scenario-level specificity resulted in the exclusion of over a dozen studies, and over a hundred scenarios. Even after we excluded aggregated data, the current three meta-analyses still had to analyze a highly heterogeneous sample of scenarios. As such, random-effects models weighted study-level variances nearly equally, changing the degrees of freedom from the scenario-level (120+ observations) to the study-level (7 to 8 observations). This loss in degrees of freedom precluded the ability to test for more intricate interactions in the data (Lipsitz, Ibrahim and Parzen, 1999). These results illustrated that the meta-analyses of highly heterogeneous studies may be less interpretable and useful than initially anticipated.

Third, subgroup differences under the common effect model suggest that missing data (i.e., ties) might have some impact on the results of safe bet choice. A reason may be that more subjects in the low ratio group ($n = 32$) withdrew from the studies compared with those in the high ratio group ($n = 18$). If these subjects were lost to follow-up, their preferred responses were not seen, and the safe bet choice in these studies was underestimated. For example, Guo (2021) with a larger number of missing data in the low ratio group ($n = 17$) had rather small estimates of safe bet choice. Besides, across both the two-level models tested, the summary estimate of τ^2 in the binary choice meta-analysis was negligible. This means that the models were not able to account for the unexplained variances observed between studies. It also suggests that there may be other, albeit unexamined, between-study factors that influenced the magnitudes of safe bet choice sizes observed.

From a methodological standpoint, the current meta-analyses were limited in two ways. First and practically, we summarized the sizes of safe bet choice, predicted, or unpredicted PR at either the low or high loss or gain ratio level within studies before summarizing the sizes over studies, by simply calculating the average size for each ratio level using an unweighted average. While the averaging method overcomes the complexity of scenario-level comparisons between the two ratio levels per experiment or treatment, the standard error of the average observed size may differ from the sampling variance of an individual observed size. Second, under bilateral ("split-body") interventions, multiple scenarios that were correlated from each participant in each experiment or treatment require the use of robust variance estimation. However, it is still challenging for this multivariate method to detect small effect sizes at the meta-analysis level.

10. General discussion

The PR phenomenon occurs if individuals state contradictory preference orderings over two options when different but formally equivalent and incentive compatible procedures are used to elicit them. PR between choice and price valuation is one of the most studied violations of rationality. In this research, we explicitly conducted three standard PR experiments with three treatments, one relying on monetary scales of loss ratios within pairs of bets, and the other two focusing on monetary scales of EVs across and within pairs of bets, respectively. In this regard, we explored a novel explanation of the asymmetrical reversal pattern from the perspective of the magnitude of loss ratios of bet pairs. We also conducted a fourth experiment relative to choice preferences in the framework of the PR phenomenon. We manipulated the size and distribution of payoffs in a set of mixed bets complying to the criteria of several heuristic strategies, using cumulative prospect theory as the benchmark, to examine magnitude effects of risk preference *within* a battery of choices (not on subsequent choices). Taken together, these allowed us to test whether various aspects of the stake size within and across pairs of bets result in different patterns of PR.

The experiments reported in this research were designed mainly to test several hypotheses: (1) incidence of predicted reversals is reduced if bet pairs have low loss ratios, where reversers are subjected to the risk-seeking behavior that causes them to prefer \$-bets; (2) heuristic strategies such as the loss-averse and majority rules explain certain binary choice preferences; (3) higher EVs between bet pairs cause more reversal rates; (4) higher EVDs within bet pairs cause less contextual reversal rates; and (5) greater accuracy in memory retrieval correlates with lower rates of PR. We preliminarily confirmed Hypotheses (1) and (2) above, while Hypotheses (3) and (4) were only weakly confirmed at best. Although reversal frequency was reduced in one condition, it stayed at approximately the same level in the other conditions. Hypothesis (5) was strongly confirmed. Results of the third and fourth experiments showed that that subjects displayed substantially fewer reversals if they were able to correctly recollect their choice decisions. They were able to persist with their preferences from the initial choice task to the subsequent price one. It seems, then, that the PR phenomenon is vulnerable to the magnitudes of loss ratio and is coupled with episodic memory of choice preference. These are no doubt the most important findings of the current research.

While some critics have been accumulated toward the interpretation of PR as revealing pathological inconsistency by Kahneman and colleagues (e.g., Arkes, Gigerenzer and Hertwig, 2016; Gigerenzer, 2004; Smith, 2003), our empirical findings suggest another piece of evidence that bounded episodic memory capacity rather than logical inconsistency per se may, at least partially, explain PR. We argue that this explanation is consistent with one among other definitions of ecological rationality apart from logical consistency. Of course, the research as it is still leaves many important questions unanswered. We do not know to what extent the magnitude effect of loss or gain ratio and EV will be endowed with other types of gambles (e.g., multiple-outcome lotteries) and of decisions (e.g., health cares, intertemporal choices). Will subjects be able to apply the same manners to the other gain-zero and loss-zero designs that are of the same nature as the ones played here but have very different formats? In real life situations, if the payoffs at stake are very large, or the market-like environment is activated, will they still react to information transmitted to them persistently? A large body of literature has already explored these questions, but more empirical findings would still be needed to scrutinize the relative effectiveness of alternative hypotheses.

11. Summary, limitations, and future directions

11.1. Summary of findings

To sum the findings, the research presents three experiments on the PR phenomenon and another one on binary choice tasks of PR, with a main focus on differences in the loss domains between bet pairs in a series of lotteries. Experiment 1: Magnitude effects in PR extended previously limited research on trade-off magnitude PR, studying how loss ratios of lotteries affect likelihoods of risk preference as well as rates of predicted and unpredicted PR. The experiment advanced this literature by showing that, first, loss ratios between bet pairs are likely to affect risk-averse versus risk-seeking preference within choice instead of price tasks. Second, the inclination of judging the $-bet higher than the P-bet is more stable either within price than choice tasks, or for the bet pairs with high rather than low loss ratios. Third, new insights are provided into how the magnitude of the loss variation between bet pairs shows an important impact on the rates of predicted PR. In particular, reducing this variation to a certain extent can lessen predicted PR, such that the loss variation has roughly two times as powerful as the same amount of gain variation does to reduce predicted PR rates. This pattern, we argue, is direct evidence of the context-dependent nature of PR as ubiquitously influenced by loss aversion.

Experiment 2: Binary choices in PR found that when the loss ratio is more than -3.0, proportions of choices—substantial and well above chance level—were in the direction predicted by cumulative prospect theory and the loss-averse rule of decision rather than by another two heuristic rules, at both the conditional and aggregate levels. These results suggest that when loss risk reaches a level of threshold, risk behavior for binary choices on lotteries is still best accounted for by a compensatory manner of value maximization such as cumulative prospect theory or by a non-compensatory and information-ignoring strategy such as the loss-averse rule.

Overall, both Experiment 3: Episodic memory in PR and Experiment 4: Episodic memory in attraction effect PR extended the sparse literature by providing evidence that EVDs and episodic memory affect PR. The first empirical finding grows out of data reconfirming the main conclusions that we drew in Experiment 1: Magnitude effects in PR. The second showed some trends that a relatively high EV in a given bet pair is likely to yield more predicted PR, as evidenced by preferential choices for P-bets but overpricing $-bets higher than P-bets. However, 50% and 100% EVDs within bet pairs are likely to provide only equivocal success in truncating contextual PR when attraction decoys are present. The third and main empirical finding figures out how retrieval operates behind the information processing of PR, with fuzzy-trace theory being illustrative of this idea; that is, greater accuracy in retrieval of initial choices correlates with lower rates of PR, as evidenced by fewer inconsistencies between initial choices and subsequent price judgments.

In three meta-analyses of 12 experiments or treatments reported by 7 prior and current studies (N = 884), Binary choice and PR: Three meta-analyses showed that neither low nor high loss or gain ratios are more powerful—a finding counter to the data reported in Experiment 1: Magnitude effects in PR and Experiment 3: Episodic memory in PR. We also identified no indications that the PR design (gain-zero or gain-loss) or the evaluation mode (separate or join) influences safe bet choice and PR sizes. As the first meta-analytic research on this phenomenon, we reasoned possible factors that may cause those conflicting results.

11.2. Limitations

The current research is not without limitations. First, we attempted to neutralize the effect of probability and EV to focus on risk preferences and judgments on various aspects of an outcome. However, the sets of lotteries used in the experiments are not very rich. Moreover, we admit that it was the fault of our experimental design in Experiment 1: Magnitude effects in PR that the numbers of lotteries and participants per lottery set as a between-subjects variable were uneven. So care should be taken not to overestimate the results. Second, given that we manipulated stimulus bets with regard to their loss ratios rather than gain ratios, a similar manipulation yielding a range of equidistantly increased gain ratios in gain-zero and gain-loss designs should be replicated in order to retest the generality of our hypotheses.

Third, in Experiment 1: Magnitude effects in PR, Experiment 3: Episodic memory in PR, and Experiment 4: Episodic memory in attraction effect PR, we followed the timeline of a typical PR procedure in the literature by asking our participants to first undertake the choice task, that is, to make a straight choice while viewing a pair of bets, and then the price task, that is, to place a minimum selling or maximum buying price on the P-bet and $-bet (e.g., Berg et al., 1985, 2010; Casey, 1991; Grether and Plott, 1979; Lichtenstein and Slovic, 1971; Pommerehne et al., 1982). Although we counterbalanced the lottery options within each task, one could argue that this strictly sequential ordering setup may create a very special information processing and then have an unintended biasing effect. Fourth, the use of a large number of the commercial products, say, forty Vespa motorcycle, as a reward in Experiment 3: Episodic memory in PR instead of hypothetical money may probably be somehow beyond the imagination of the respondents.

Fifth, Experiment 1: Magnitude effects in PR and partial Experiment 2: Binary choices in

PR used hypothetical gambling bets, as this purely hypothetical judgment method has been common and acceptable in psychological research. Notwithstanding that the participants were given explicit instructions on the meaning of choice or willingness-to-pay price, they may show to a certain extent an insufficient willingness to participate due to the lack of the so-called "play-out" and "payment" effects (Berg et al., 2013). As a result, they might not have thought carefully about which choice or what price would reflect their own preferences. If the choice or price that they stated had instead monetary or some sort of positive consequences for making good decisions, they might think more carefully about their prices and assign them more in line with their choices.

Note that economists tend to prefer the so-called "incentive compatible" mechanism in order to ensure sufficient response rates and truth-telling. Actually, neither approach is fool-proof. For instance, incentive-aligned tasks in experiments often induce biasing effects such as the so-called house money effect, a robust phenomenon that when cash incentives are provided in the beginning of surveys, then prior gains increase a tendency to accept risky gambles (Thaler and Johnson, 1990). Moreover, other studies did not find evidence supporting the superiority of incentivized measures (Eckel, 2019; Enke, Gneezy, Hall, Martin, Nelidov, Offerman and van de Ven, 2020). Besides, although the participants were incentivized, and their decisions were also not hypothetical in Experiment 4: Episodic memory in attraction effect PR, it is not to say that the data quality and structure were not potentially affected by respondents' lack of required attention and speedy response patterns by virtue of the online survey that we implemented.

11.3. Future directions

In this section, we outline possible avenues for future research. First, researchers may increase the salience of the counterfactual probabilities and payoffs in the chosen lottery, to see if this could influence risk preferences as well as predicted and unpredicted PR. In addition, more research is necessary to find out if, and to what extent, possible payoffs can override the preference to a bet with a higher EV.

Second, recent research relating to experience-based tasks identified that individual stability in risk preference is vulnerable to past and current decision-making environments of loss and gain payoffs (Gal and Rucker, 2018; Lee and Daunizeau, 2021; Rakow, Cheung and Restelli, 2020), as well as to credence (vs. experience) attributes for those people who view personal qualities as fixed (Roy and Naidoo, 2021). This is because decision makers evaluate risky events by relying on both contextual descriptions and retrospective experience (Kusev, van Schaik, Ayton, Dent and Chater, 2009). In the real world, experience-based tasks are even more common than description-based tasks, since there is often a lack of descriptive information (Hertwig, Barron, Weber and Erev, 2004). Although it is intriguing to know whether the current experimental data can also predict this plasticity in risk preference, it was not a primary research aim to test this. Therefore, our findings need to be investigated in such as temporal environments, where intertemporal choices can be examined dynamically (Busemeyer and Townsend, 1993; Johnson and Busemeyer, 2005; Sugden, 2021). By so doing, we can examine discount rates of loss-related risk preferences in a temporal PR experiment.

Third, it is needed to explore the influence of episodic memory on PR by manipulation of participants' psychological perspective. We can hypothesize that a general perspective of thinking could diminish recollecting and favor reconstructing an event's details based on schematic knowledge or gist of this event; moreover, it also helps to reduce confusion between pieces of information and prompts organization of items. Concrete perspective, by contrast, favors precise or verbatim recollection of previous judgments and facts rather than their reconstruction. It is also more likely to become distracted and confused with new information (cf., Fukukura, Ferguson and Fujita, 2013). We can base these assumptions on theories known in the domains of memory (e.g., the fuzzy-trace theory) and social/cognitive psychology research (e.g., the construal level theory).

Practically, future research may include the following two conditions that can show a link between episodic memory and PR directly. In one condition, we can make information of all previous choices available to participants during the sessions so that limited episodic memory could not influence the choice behavior. In another condition, we can replicate the sessions we run in Experiment 3: Episodic memory in PR and Experiment 4: Episodic memory in attraction effect PR, where limited episodic memory might influence PR. Then, we would expect to see more PR rates in the first condition that requires episodic memory.

Fourth, future research may also investigate whether contextual factors, such as evaluation modes, can moderate magnitude effects in PR. To date, rare research has put forth whether joint and separate evaluations could shed light on contextual PR. An exception is Cheng, Yu, Huang and Dai (2017), which showed that (1) adding an attraction decoy A_T or a compromise decoy B_T produces a weaker PR effect (as measured by the amount of subtracting the willingness-to-accept price of the T from the willingness-to-pay of the C) in joint $\{T,\ C,\ A_T\}$ or $\{T,\ C,\ B_T\}$ evaluation compared to joint $\{T,\ C\}$ evaluation; and (2) adding an attraction decoy A_C or a compromise deocy B_C produces a greater PR effect within joint $\{T,\ C,\ A_C\}$ or $\{T,\ C,\ B_C\}$ evaluation compared to joint $\{T,\ C\}$ evaluation (cf.,

Figure 3). However, this PR effect differs from a classic PR in that the latter is computed as the proportion of choosing one option while placing a higher price on another. Also, Cheng and colleagues used non-bets (e.g., a physically inferior dictionary with more entries vs. a new dictionary with less entries) as stimuli and implemented only choice tasks.

Thus, it would be interesting, and left for future research, to investigate these findings in a conventional manner, that is, by means of both implementing gambling bets as stimuli and eliciting risk preferences within choice and price tasks. More precisely, future research may examine the following six hypotheses: (1) Adding an attraction decoy A_T causes less PR in joint $\{T,\ C,\ A_T\}$ evaluation compared to joint $\{T,\ C\}$ evaluation; (2) Adding an attraction decoy A_C causes more PR in joint $\{T,\ C,\ A_C\}$ evaluation compared to joint $\{T,\ C\}$ evaluation; (3) Adding a compromise decoy B_T causes less contextual PR in joint $\{T,\ C,\ B_T\}$ evaluation compared to joint $\{T,\ C\}$ evaluation; (4) Adding a compromise decoy B_C causes more contextual PR in joint $\{T,\ C,\ B_C\}$ evaluation compared to joint $\{T,\ C\}$ evaluation; (5) Adding a similarity decoy S_T causes less contextual PR in joint $\{T,\ C,\ S_T\}$ evaluation compared to joint $\{T,\ C\}$ evaluation; and (6) Adding a similarity decoy S_C causes more contextual PR in joint $\{T,\ C,\ S_C\}$ evaluation compared to joint $\{T,\ C\}$ evaluation.

12. Conclusion

To conclude, the current research yielded several findings of general significance. In the PR literature, it would be easy to draw the conclusion that a "hard-wired" information processing limitation results in the robustness of the PR phenomenon. However, the present work implicates contingent encoding processes which, under certain circumstances, shift as a function of size of stakes and lead to a predictable pattern of reversal. For bets that have low loss ratios, expectation levels appear to have increased influence relative to risk preferences within the choice task and to the PR types. This research has implications for assisting individuals in evaluating risky decision situations. However, as these experiments we examined used completely different sets of bets, the results we present might also be attributed to differences in bets across experiments.

For the first time we attempted to demonstrate that false episodic memory like the distortion of recalling preferential choices manifests the possible cause of PR. The findings add to the growing evidence for the empirical validity of memory-based process in a preferential domain, rendering processes that involve memory a viable alternative to classic logic explanations of inconsistency between choice and certainty equivalent. Individuals exhibit less PR rates when they could correctly recollect their preferential choices. What is key is that the memory-based process view specifies how past episodic scenarios influence the preference for the same options in a subsequently different elicitation procedure. We argue that the negative correlation between subjects' accuracy of memory retrieval and rates of PR evidences that differences across subjects' memory capacity can explain some observed variation in rates of PR. This suggests that we should be cautious in attributing PR to logical inconsistency but should instead attribute PR, at least partially, to bounded memory capacity.

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Appendix A. A formal framework of the loss-averse rule

Consider a choice problem with a choice set of $\mathcal{A} = \{A_1, ..., A_n\}$, where A_i are risky prospects (bets) defined over an M-dimensional state space $\mathbb{S} = \{1, ..., m\}$ with objective and known probabilities, $p_{i,j}$, for each $j \in \mathbb{S}$ such that $\sum_{j=1}^{m} p_{i,j} = 1$, $i \in \mathbb{N} = 1, ..., n$. The payoffs of Bet A_i are given with the payoff vector $v_i = (v_{i,1}, ..., v_{i,m})$. The loss-averse parameter la in a given pair of bets $A_{i_1} = (v_{i_1,1}, p_{i_1,1}; ...; v_{i_1,j_1}, p_{i_1,j_1}; ...; v_{i_1,m}, p_{i_1,m})$ and $A_{i_2} = (v_{i_2,1}, p_{i_2,1}; ...; v_{i_2,j_2}, p_{i_2,j_2}; ...; v_{i_2,m}, p_{i_2,m})$ is captured by a continuous and bounded function $la(v_{i_1,j_1}, v_{i_2,j_2})$, where v_{i_1,j_1} and v_{i_2,j_2} are the payoff vectors for Bets A_{i_1} and A_{i_2}, respectively.

Let $la(v_{i_1,j_1}, v_{i_2,j_2}) = -\dfrac{v_{i_2,j_2}}{v_{i_1,j_1}}$, where $v_{i_2,j_2} \leqslant v_{i_1,j_1} < 0$, $i_1, i_2 \in \mathbb{N}$, and $j_1, j_2 \in \mathbb{S}$.

According to the loss-averse rule, decisions are not made in a vacuum, but rather in a multidimensional context, where the attributes of a risky prospect are compared with the features of other available alternatives. Specifically, the loss-averse thinker chooses a bet according to the bets' perceived loss-averse parameter la: (1) If $la(v_{i_1,j_1}, v_{i_2,j_2}) \leqslant -t$, in which t is a level of threshold above zero, Bet A_{i_1} or A_{i_2} is chosen; (2) If $la(v_{i_1,j_1}, v_{i_2,j_2}) > -t$, Bet A_{i_1} is chosen; both for all $i_1, i_2 \in \mathbb{N}$ and $j_1, j_2 \in \mathbb{S}$. Notice that these decisions are distorted to some extent from their intrinsic payoffs, since they are inflated at the expense of the gain payoffs of the bets.

Appendix B. A formal framework of the majority rule[4]

Let $\mathcal{A} = \{A_1, \ldots, A_n\}$ be a finite set of multidimensional statements.

Let $\mathbb{S} = \{1, \ldots, m\}$ be an M-dimensional subjective space where the $\mathcal{A}$ is represented, satisfying that A_i can and only can be represented as the ith point in the M-dimension space.

The statement A_i is characterized on the M dimensions and is then of the form $A_i = (\mathrm{O}_{i,1}, \ldots, \mathrm{O}_{i,m})$, where $\mathrm{O}_{i,j}$ ($j = 1, \ldots, \mathrm{m}$) is the objective value level of Statement A_i on Dimension j. More specifically, either level of Dimension j in the case of Statement A_i undergoes a transformation which is a monotonic utility function $u_{ij} = U_j^{t,p}\ (\mathrm{O}_{i,j})$ where p is the person who generates the function over a certain time interval t, representing the subjective value of j^{th} component of Statement A_i that is estimated by the person. Note that $U_j^{t,p}\ (\mathrm{O}_{i,j})$ may be any kind of scale (e.g., nominal, ordinal, interval, or ratio scale values).

Let

$$U_{jm}^{t,p}(O_{i_1,j_1}) = \begin{cases} 0 & \text{if } \mathrm{U}_j^{t,p}\ (\mathrm{O}_{i_1,j_1}) \preccurlyeq_L U_j^{t,p}\ (\mathrm{O}_{i_2,j_2}) \\ 1 & \text{if } \mathrm{U}_j^{t,p}\ (\mathrm{O}_{i_1,j_1}) \succ_L U_j^{t,p}\ (\mathrm{O}_{i_2,j_2}),^{5} \end{cases} \quad i_1, i_2 = 1, \ldots, n; j_1, j_2 = 1, \ldots, m,$$

and

$U_{j_{sum}}^{t,p}\ (\mathrm{O}_{i,j}) = \sum_{i=1}^{n}\sum_{j=1}^{m} U_{jm}^{t,p}\ (\mathrm{O}_{i,j}),\ i = 1, \ldots, n;\ j = 1, \ldots, m.$

[4]The description first appeared in Lu and Nieznański (2017) and was done with the help of Revd Prof. Marek Porwolik at the Institute of Philosophy, Faculty of Christian Philosophy, Cardinal Stefan Wyszyński University in Warsaw.

[5]The notations "$\preccurlyeq_{\mathrm{L}}$" and "$\succ_{\mathrm{L}}$" rather than "$\succcurlyeq$" and "$\succ$" are used to emphasize that the decision maker's judgment may or may not satisfy the utility theory. The notations "$\preccurlyeq$" and "$\succ$" indicate that the axioms are satisfied according to utility theory's definition.

Suppose

$$\begin{pmatrix} U_{\text{sum}}^{t,p}(O_{1,j}) \\ U_{\text{sum}}^{t,p}(O_{2,j}) \\ \dots \\ U_{\text{sum}}^{t,p}(O_{n,j}) \end{pmatrix} = \begin{pmatrix} \sum_{j=1}^{m} U_{j\text{sum}}^{t,p}(O_{1,j}) \\ \sum_{j=1}^{m} U_{j\text{sum}}^{t,p}(O_{2,j}) \\ \dots \\ \sum_{j=1}^{m} U_{j\text{sum}}^{t,p}(O_{n,j}) \end{pmatrix}.$$

If the person employs the majority rule for all $j \in \mathbb{S}$ to compare A_{i_1} and A_{i_2}, where A_{i_1}, $A_{i_2} \in \mathcal{A}$ and i_1, $i_2 \in \{1, ..., n\}$, then *majority dominance* is said to be hold. More specifically, (1) when $U_{\text{sum}}^{t,p}$ $(\mathrm{O}_{2,j}) \succ_{\mathrm{L}}$ $U_{j\mathrm{m}}^{t,p}$ $(\mathrm{O}_{1,j})$, that is, if and only if the total number of preference dominance for which A_2 is "better than" A_1 exceeds the total number of preference dominance for which A_1 is "better than" A_2, then A_2 is majority preferred to A_1; and (2) when $U_{\text{sum}}^{t,p}$ $(\mathrm{O}_{2,j})$ $=$ $U_{j\mathrm{m}}^{t,p}$ $(\mathrm{O}_{1,j})$, that is, if and only if the total number of preference dominance for which A_2 is preferred to A_1 is equal to the total number of preference dominance for which A_1 is preferred to A_2, then A_{i_2} is equally preferred to A_{i_1}.

Appendix C. Propositions and conjectures: Formal definitions and existences

The following propositions (cf., Table 3) are proved regarding, by definition, P-bet = $(p_{\mathrm{P}},\ v^{+}_{\mathrm{P}};\ 1 - p_{\mathrm{P}},\ v^{-}_{\mathrm{P}})$ and \$-bet = $(p_{\$},\ v^{+}_{\$},\ 1 - p_{\$},\ v^{-}_{\$})$, where $(\forall\ p_{\mathrm{P}},\ p_{\$},\ v^{+}_{\mathrm{P}},\ v^{-}_{\mathrm{P}},\ v^{+}_{\$},\ v^{-}_{\$} \in \mathbb{R})$ $(\exists\ 1 > p_{\mathrm{P}} > p_{\$} > 0,\ v^{+}_{\mathrm{P}},\ v^{+}_{\$} > 0 > v^{-}_{\mathrm{P}},\ v^{-}_{\$})$ $p_{\mathrm{P}}v^{+}_{\mathrm{P}} + (1 - p_{\mathrm{P}})v^{-}_{\mathrm{P}} = p_{\$}v^{+}_{\$} + (1 - p_{\$})v^{-}_{\$}$, viz., the EVs of the P-bet and \$-bet are equivalent. As outlined in Section 2.2, for simplicity, the relations between the payoffs v^{+}_{P} and $v^{+}_{\$}$ and between the payoffs v^{-}_{P} and $v^{-}_{\$}$ are more generally defined, namely $v^{+}_{\mathrm{P}},\ v^{+}_{\$} > 0 > v^{-}_{\mathrm{P}},\ v^{-}_{\$}$, instead of $v^{+}_{\$} > v^{+}_{\mathrm{P}} > 0 > v^{-}_{\mathrm{P}} > v^{-}_{\$}$.

Proposition 1.1. $(\exists\ v^{+}_{\mathrm{P}} = v^{+}_{\$},\ v^{+}_{\mathrm{P}} > v^{-}_{\$},\ v^{-}_{\$} > v^{-}_{\mathrm{P}},\ p_{\mathrm{P}} - p_{\$} > 1 - p_{\mathrm{P}})$ $v^{-}_{\$} - v^{-}_{\mathrm{P}} > v^{+}_{\mathrm{P}} - v^{-}_{\$}$.

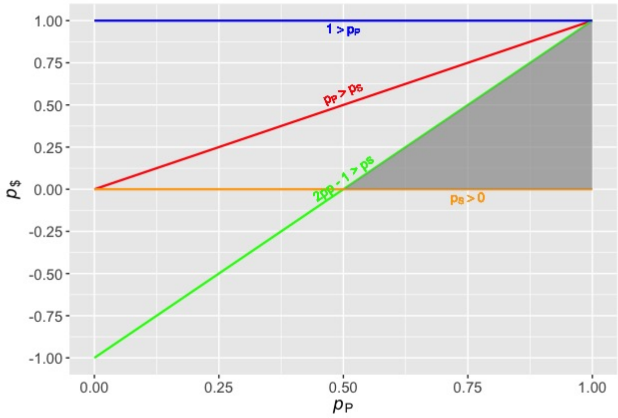
Proof. Suppose $v^{+}_{\mathrm{P}} > v^{-}_{\$}$. Then $v^{+}_{\mathrm{P}} - v^{-}_{\$} > 0$. Likewise, suppose $v^{-}_{\$} > v^{-}_{\mathrm{P}}$. Then $v^{-}_{\$} - v^{-}_{\mathrm{P}} > 0$. Suppose $v^{+}_{\mathrm{P}} = v^{+}_{\$}$. Then $p_{\mathrm{P}}v^{+}_{\mathrm{P}} + (1 - p_{\mathrm{P}})v^{-}_{\mathrm{P}} = p_{\$}v^{+}_{\$} + (1 - p_{\$})v^{-}_{\$} \iff p_{\mathrm{P}}v^{+}_{\mathrm{P}} + (1 - p_{\mathrm{P}})v^{-}_{\mathrm{P}} = p_{\$}v^{+}_{\mathrm{P}} + (1 - p_{\$})v^{-}_{\$} \iff (p_{\mathrm{P}} - p_{\$})(v^{+}_{\mathrm{P}} - v^{-}_{\$}) = (1 - p_{\mathrm{P}})(v^{-}_{\$} - v^{-}_{\mathrm{P}})$. Suppose $p_{\mathrm{P}} - p_{\$} > 1 - p_{\mathrm{P}} > 0$. Thus the statement $v^{-}_{\$} - v^{-}_{\mathrm{P}} > v^{+}_{\mathrm{P}} - v^{-}_{\$}$ is true.

Specifically, on the one hand, suppose $p_{\$} = 1 - p_{\mathrm{P}}$. Then $p_{\mathrm{P}} - p_{\$} > 1 - p_{\mathrm{P}} \iff p_{\mathrm{P}} - (1 - p_{\mathrm{P}}) > 1 - p_{\mathrm{P}} \iff p_{\mathrm{P}} > \frac{2}{3}$. On the other hand, suppose $1 > p_{\mathrm{P}} > p_{\$} > 0$ and $p_{\mathrm{P}} - p_{\$} > 1 - p_{\mathrm{P}}$. Thus the constraints of $p_{\$}$ are as follows: $p_{\$} > 0$, $p_{\mathrm{P}} > p_{\$}$, $1 > p_{\$}$, and $2p_{\mathrm{P}} - 1 > p_{\$}$ (see Figure C.22a). $\square$

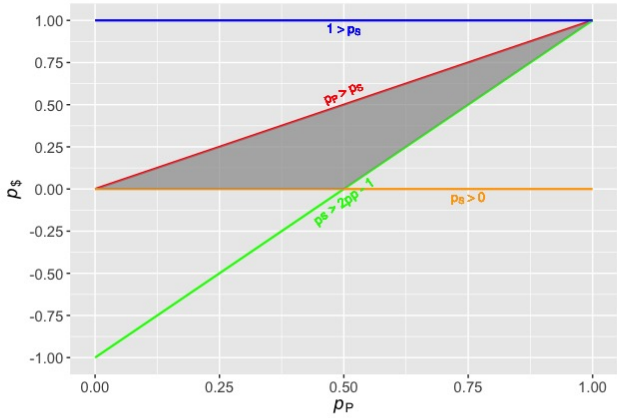
Proposition 1.2. $(\exists\ v^{+}_{\mathrm{P}} = v^{+}_{\$},\ v^{+}_{\mathrm{P}} > v^{-}_{\$},\ v^{-}_{\$} > v^{-}_{\mathrm{P}},\ 1 - p_{\mathrm{P}} > p_{\mathrm{P}} - p_{\$})$ $v^{+}_{\mathrm{P}} - v^{-}_{\$} > v^{-}_{\$} - v^{-}_{\mathrm{P}}$.

Proof. Suppose $v^{+}_{\mathrm{P}} > v^{-}_{\$}$. Then $v^{+}_{\mathrm{P}} - v^{-}_{\$} > 0$. Likewise, suppose $v^{-}_{\$} > v^{-}_{\mathrm{P}}$. Then $v^{-}_{\$} - v^{-}_{\mathrm{P}} > 0$. Suppose $v^{+}_{\mathrm{P}} = v^{+}_{\$}$. Then $p_{\mathrm{P}}v^{+}_{\mathrm{P}} + (1 - p_{\mathrm{P}})v^{-}_{\mathrm{P}} = p_{\$}v^{+}_{\$} + (1 - p_{\$})v^{-}_{\$} \iff p_{\mathrm{P}}v^{+}_{\mathrm{P}} + (1 - p_{\mathrm{P}})v^{-}_{\mathrm{P}} = p_{\$}v^{+}_{\mathrm{P}} + (1 - p_{\$})v^{-}_{\$} \iff (p_{\mathrm{P}} - p_{\$})(v^{+}_{\mathrm{P}} - v^{-}_{\$}) = (1 - p_{\mathrm{P}})(v^{-}_{\$} - v^{-}_{\mathrm{P}})$. Suppose $1 - p_{\mathrm{P}} > p_{\mathrm{P}} - p_{\$} > 0$. Thus the statement $v^{+}_{\mathrm{P}} - v^{-}_{\$} > v^{-}_{\$} - v^{-}_{\mathrm{P}}$ is true.

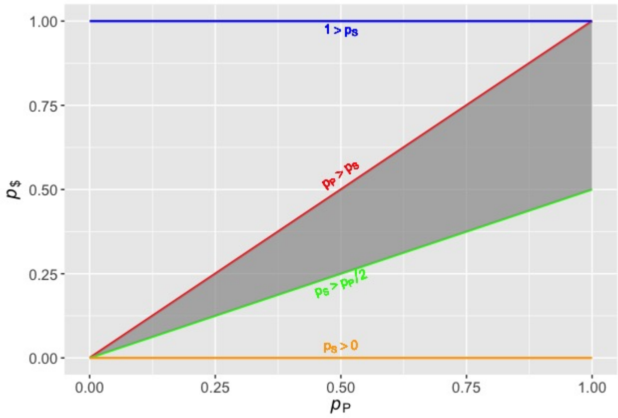
Specifically, on the one hand, suppose $p_{\$} = 1 - p_{\mathrm{P}}$. Then $1 - p_{\mathrm{P}} > p_{\mathrm{P}} - p_{\$} \iff 1 - p_{\mathrm{P}} > p_{\mathrm{P}} - (1 - p_{\mathrm{P}}) \iff \frac{2}{3} > p_{\mathrm{P}}$. On the other hand, suppose $1 > p_{\mathrm{P}} > p_{\$} > 0$ and $1 - p_{\mathrm{P}} >$



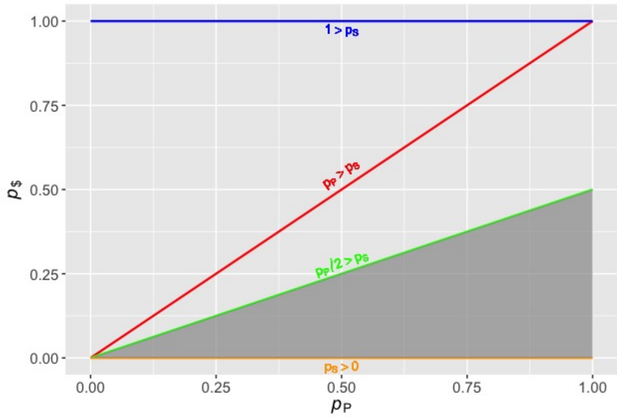
(a) Proposition 1.1



(b) Proposition 1.2



(c) Proposition 3.1



(d) Proposition 3.2

Figure C.22: Constraints of $p_\$$ (shadow triangle).

$p_P - p_\$$. Thus the constraints of $p_\$$ are as follows: $p_\$ > 0$, $p_P > p_\$$, $1 > p_\$$, and $p_\$ > 2p_P - 1$ (see Figure C.22b). □

Proposition 2. Not $((\exists\ v_P^+ = v_\$^+,\ v_P^- \geqslant v_\$^-) \implies v_P^+ > v_\$^-)$.

Proof. Suppose $v_P^+ = v_\$^+$. Then $p_P v_P^+ + (1 - p_P)v_P^- = p_\$ v_\$^+ + (1 - p_\$)v_\$^- \iff p_P v_P^+ + (1 - p_P)v_P^- = p_\$ v_P^+ + (1 - p_\$)v_\$^- \iff (p_P - p_\$)v_P^+ = (1 - p_\$)v_\$^- - (1 - p_P)v_P^-$. Suppose $0 > v_P^- \geqslant v_\$^-$, $1 - p_\$ > 0$, and $1 - p_P > 0$. Then $(1 - p_\$)v_\$^- - (1 - p_P)v_\$^- \geqslant (p_P - p_\$)v_P^+ \iff (p_P - p_\$)v_\$^- \geqslant (p_P - p_\$)v_P^+ \iff v_\$^- \geqslant v_P^+$. Thus the statement $v_P^+ > v_\$^-$ is false. (Notice that when $p_\$ > p_P$ or the EVs of the P-bet and \$-bet are not equivalent, the statement $v_P^+ > v_\$^-$ is true.) □

Proposition 3.1. $(\exists\ v_\$^+ > v_P^+,\ v_P^+ > v_\$^-,\ v_P^- = v_\$^-,\ p_\$ > p_P - p_\$)$ $v_P^+ - v_\$^- > v_\$^+ - v_P^+$.

Proof. Suppose $v_{\$}^{+} > v_{P}^{+}$. Then $v_{\$}^{+} - v_{P}^{+} > 0$. Likewise, suppose $v_{P}^{+} > v_{\$}^{-}$. Then $v_{P}^{+} - v_{\$}^{-} > 0$. Suppose $v_{P}^{-} = v_{\$}^{-}$. Then $p_{P}v_{P}^{+} + (1 - p_{P})v_{P}^{-} = p_{\$}v_{\$}^{+} + (1 - p_{\$})v_{\$}^{-} \iff p_{P}v_{P}^{+} + (1 - p_{P})v_{\$}^{-} = p_{\$}v_{\$}^{+} + (1 - p_{\$})v_{\$}^{-} \iff (p_{P} - p_{\$})(v_{P}^{+} - v_{\$}^{-}) = p_{\$}(v_{\$}^{+} - v_{P}^{+})$. Suppose $p_{\$} > p_{P} - p_{\$} > 0$. Thus the statement $v_{P}^{+} - v_{\$}^{-} > v_{\$}^{+} - v_{P}^{+}$ is true.

Specifically, on the one hand, suppose $p_{\$} = 1 - p_{P}$. Then $p_{\$} > p_{P} - p_{\$} \iff 1 - p_{P} > 1 - (1 - p_{P}) \iff \frac{2}{3} > p_{P}$. On the other hand, suppose $1 > p_{P} > p_{\$} > 0$ and $p_{\$} > p_{P} - p_{\$}$. Thus the constraints of $p_{\$}$ are as follows: $p_{\$} > 0$, $p_{P} > p_{\$}$, $1 > p_{\$}$, and $p_{\$} > \frac{p_{P}}{2}$ (see Figure C.22c). □

Proposition 3.2. $(\exists\ v_{\$}^{+} > v_{P}^{+},\ v_{P}^{+} > v_{\$}^{-},\ v_{P}^{-} = v_{\$}^{-},\ p_{P} - p_{\$} > p_{\$})\ v_{\$}^{+} - v_{P}^{+} > v_{P}^{+} - v_{\$}^{-}$.

Proof. Suppose $v_{\$}^{+} > v_{P}^{+}$. Then $v_{\$}^{+} - v_{P}^{+} > 0$. Likewise, suppose $v_{P}^{+} > v_{\$}^{-}$. Then $v_{P}^{+} - v_{\$}^{-} > 0$. Suppose $v_{P}^{-} = v_{\$}^{-}$. Then $p_{P}v_{P}^{+} + (1 - p_{P})v_{P}^{-} = p_{\$}v_{\$}^{+} + (1 - p_{\$})v_{\$}^{-} \iff p_{P}v_{P}^{+} + (1 - p_{P})v_{\$}^{-} = p_{\$}v_{\$}^{+} + (1 - p_{\$})v_{\$}^{-} \iff (p_{P} - p_{\$})(v_{P}^{+} - v_{\$}^{-}) = p_{\$}(v_{\$}^{+} - v_{P}^{+})$. Suppose $p_{P} - p_{\$} > p_{\$} > 0$. Thus the statement $v_{\$}^{+} - v_{P}^{+} > v_{P}^{+} - v_{\$}^{-}$ is true.

Specifically, on the one hand, suppose $p_{\$} = 1 - p_{P}$. Then $p_{P} - p_{\$} > p_{\$} \iff p_{P} - (1 - p_{P}) > 1 - p_{P} \iff p_{P} > \frac{2}{3}$. On the other hand, suppose $1 > p_{P} > p_{\$} > 0$ and $p_{P} - p_{\$} > p_{\$}$. Thus the constraints of $p_{\$}$ are as follows: $p_{\$} > 0$, $p_{P} > p_{\$}$, $1 > p_{\$}$, and $\frac{p_{P}}{2} > p_{\$}$ (see Figure C.22d). □

Proposition 3.3. $(\exists\ v_{\$}^{+} > v_{P}^{+},\ v_{P}^{+} > v_{\$}^{-},\ v_{P}^{-} = v_{\$}^{-},\ p_{\$} = p_{P} - p_{\$})\ v_{P}^{+} - v_{\$}^{-} = v_{\$}^{+} - v_{P}^{+}$.

Proof. Suppose $v_{\$}^{+} > v_{P}^{+}$. Then $v_{\$}^{+} - v_{P}^{+} > 0$. Likewise, suppose $v_{P}^{+} > v_{\$}^{-}$. Then $v_{P}^{+} - v_{\$}^{-} > 0$. Suppose $v_{P}^{-} = v_{\$}^{-}$. Then $p_{P}v_{P}^{+} + (1 - p_{P})v_{P}^{-} = p_{\$}v_{\$}^{+} + (1 - p_{\$})v_{\$}^{-} \iff p_{P}v_{P}^{+} + (1 - p_{P})v_{\$}^{-} = p_{\$}v_{\$}^{+} + (1 - p_{\$})v_{\$}^{-} \iff (p_{P} - p_{\$})(v_{P}^{+} - v_{\$}^{-}) = p_{\$}(v_{\$}^{+} - v_{P}^{+})$. Suppose $p_{\$} = p_{P} - p_{\$} > 0$. Thus the statement $v_{P}^{+} - v_{\$}^{-} = v_{\$}^{+} - v_{P}^{+}$ is true. □

Conjecture 4.1. $(\exists\ v_{\$}^{+} > v_{P}^{+},\ v_{P}^{+} > v_{\$}^{-},\ v_{\$}^{-} > v_{P}^{-})\ v_{\$}^{+} - v_{P}^{+} > v_{P}^{+} - v_{\$}^{-}$ and $v_{\$}^{+} - v_{P}^{+} > v_{\$}^{-} - v_{P}^{-}$.

Conjecture 4.2. ($\exists\ v_{\$}^{+} > v_{\mathrm{P}}^{+},\ v_{\mathrm{P}}^{+} > v_{\$}^{-},\ v_{\$}^{-} > v_{\mathrm{P}}^{-}$) v_{P}^{+} - $v_{\$}^{-} > v_{\$}^{+}$ - v_{P}^{+} and v_{P}^{+} - $v_{\$}^{-} > v_{\$}^{-}$ - v_{P}^{-}.

Conjecture 4.3. Not (($\exists\ v_{\$}^{+} > v_{\mathrm{P}}^{+},\ v_{\mathrm{P}}^{+} > v_{\$}^{-},\ v_{\$}^{-} > v_{\mathrm{P}}^{-}$) $\implies$ $v_{\$}^{-}$ - $v_{\mathrm{P}}^{-} > v_{\$}^{+}$ - v_{P}^{+} and $v_{\$}^{-}$ - $v_{\mathrm{P}}^{-} >$ v_{P}^{+} - $v_{\$}^{-}$).

Conjecture 5.1. ($\exists\ v_{\$}^{+} > v_{\mathrm{P}}^{+},\ v_{\mathrm{P}}^{+} > v_{\$}^{-},\ v_{\mathrm{P}}^{-} > v_{\$}^{-}$) $v_{\$}^{+}$ - $v_{\mathrm{P}}^{+} > v_{\mathrm{P}}^{+}$ - $v_{\$}^{-}$ and $v_{\$}^{+}$ - $v_{\mathrm{P}}^{+} > v_{\mathrm{P}}^{-}$ - $v_{\$}^{-}$.

Conjecture 5.2. ($\exists\ v_{\$}^{+} > v_{\mathrm{P}}^{+},\ v_{\mathrm{P}}^{+} > v_{\$}^{-},\ v_{\mathrm{P}}^{-} > v_{\$}^{-}$) v_{P}^{+} - $v_{\$}^{-} > v_{\$}^{+}$ - v_{P}^{+} and v_{P}^{+} - $v_{\$}^{-} > v_{\mathrm{P}}^{-}$ - $v_{\$}^{-}$.

Proposition 5.3. Not (($\exists\ v_{\$}^{+} > v_{\mathrm{P}}^{+},\ v_{\mathrm{P}}^{+} > v_{\$}^{-},\ v_{\mathrm{P}}^{-} > v_{\$}^{-}$) $\implies$ v_{P}^{-} - $v_{\$}^{-} > v_{\$}^{+}$ - v_{P}^{+} and v_{P}^{-} - $v_{\$}^{-}$ $>$ v_{P}^{+} - $v_{\$}^{-}$).

Proof. Suppose $v_{\mathrm{P}}^{+} > v_{\mathrm{P}}^{-}$. Then v_{P}^{+} - $v_{\$}^{-} > v_{\mathrm{P}}^{-}$ - $v_{\$}^{-}$. Thus the statement v_{P}^{-} - $v_{\$}^{-} > v_{\mathrm{P}}^{+}$ - $v_{\$}^{-}$ is false. □

Proposition 6.1. Not (($\exists\ v_{\mathrm{P}}^{+} > v_{\$}^{+},\ v_{\mathrm{P}}^{+} > v_{\$}^{-},\ v_{\$}^{-} > v_{\mathrm{P}}^{-}$) $\implies$ v_{P}^{+} - $v_{\$}^{+} > v_{\mathrm{P}}^{+}$ - $v_{\$}^{-}$ and v_{P}^{+} - $v_{\$}^{+}$ $>$ $v_{\$}^{-}$ - v_{P}^{-}).

Proof. Suppose $v_{\$}^{+} > v_{\$}^{-}$. Then v_{P}^{+} - $v_{\$}^{-} > v_{\mathrm{P}}^{+}$ - $v_{\$}^{+}$. Thus the statement v_{P}^{+} - $v_{\$}^{+} > v_{\mathrm{P}}^{+}$ - $v_{\$}^{-}$ is false. □

Conjecture 6.2. ($\exists\ v_{\mathrm{P}}^{+} > v_{\$}^{+},\ v_{\mathrm{P}}^{+} > v_{\$}^{-},\ v_{\$}^{-} > v_{\mathrm{P}}^{-}$) v_{P}^{+} - $v_{\$}^{-} > v_{\mathrm{P}}^{+}$ - $v_{\$}^{+}$ and v_{P}^{+} - $v_{\$}^{-} > v_{\$}^{-}$ - v_{P}^{-}.

Conjecture 6.3. ($\exists\ v_{\mathrm{P}}^{+} > v_{\$}^{+},\ v_{\mathrm{P}}^{+} > v_{\$}^{-},\ v_{\$}^{-} > v_{\mathrm{P}}^{-}$) $v_{\$}^{-}$ - $v_{\mathrm{P}}^{-} > v_{\mathrm{P}}^{+}$ - $v_{\$}^{+}$ and $v_{\$}^{-}$ - $v_{\mathrm{P}}^{-} > v_{\mathrm{P}}^{+}$ - $v_{\$}^{-}$.

Proposition 7. Not (($\exists\ v_{\mathrm{P}}^{+} > v_{\$}^{+},\ v_{\mathrm{P}}^{-} \geqslant v_{\$}^{-}$) $\implies$ $v_{\mathrm{P}}^{+} > v_{\$}^{-}$).

Proof. Suppose $v_{\mathrm{P}}^{+} > v_{\$}^{+}$. Then $p_{\mathrm{P}}v_{\mathrm{P}}^{+} + (1$ - $p_{\mathrm{P}})v_{\mathrm{P}}^{-} = p_{\$}v_{\$}^{+} + (1$ - $p_{\$})v_{\$}^{-} \implies p_{\$}v_{\mathrm{P}}^{+} + (1$ - $p_{\$})v_{\$}^{-} > p_{\mathrm{P}}v_{\mathrm{P}}^{+} + (1$ - $p_{\mathrm{P}})v_{\mathrm{P}}^{-} \iff (1$ - $p_{\$})v_{\$}^{-}$ - $(1$ - $p_{\mathrm{P}})v_{\mathrm{P}}^{-} > (p_{\mathrm{P}}$ - $p_{\$})v_{\mathrm{P}}^{+}$. Suppose 1 - $p_{\$} >$ 0 and $0 > v_{\mathrm{P}}^{-} \geqslant v_{\$}^{-}$. Then $(1$ - $p_{\$})v_{\$}^{-}$ - $(1$ - $p_{\mathrm{P}})v_{\$}^{-} > (p_{\mathrm{P}}$ - $p_{\$})v_{\mathrm{P}}^{+} \iff (p_{\mathrm{P}}$ - $p_{\$})v_{\$}^{-} > (p_{\mathrm{P}}$ - $p_{\$})v_{\mathrm{P}}^{+} \iff v_{\$}^{-} > v_{\mathrm{P}}^{+}$. Thus the statement $v_{\mathrm{P}}^{+} > v_{\$}^{-}$ is false. (Notice that when $p_{\$} > p_{\mathrm{P}}$, the statement $v_{\mathrm{P}}^{+} > v_{\$}^{-}$ is true.) □

Appendix D. Lists of lottery

Each lottery pair consists of four possible payoffs and their probabilities from two bets, which are expressed by the format of P-bet = (p, v_P^+; 1 - p, v_P^-) and \$-bet = (1 - p, $v_\$^+$; p, $v_\$^-$).

Appendix D.1. Pilot study (Lu, 2017) of Experiment 1: Magnitude effects in PR

Table D.17 contains the 3 lottery pairs used for preliminary evidence.

Table D.17: EVs and gain and loss ratios of the lotteries in the Pilot study (Lu, 2017) of Experiment 1: Magnitude effects in PR.

			Ratio					Ratio	
No.	Lottery	EV	Loss	Gain	No.	Lottery	EV	Loss	Gain
1	(9/12, 110; 3/12, -10) (3/12, 920; 9/12, -200)	80.0	-20.0	8.4	2	(9/12, 120; 3/12, -10) (3/12, 395; 9/12, -15)	87.5	-1.5	3.3
3	(9/12, 137; 3/12, -210) (3/12, 800; 9/12, -200)	50.25 50.0	-1.1	5.8					

Table D.18 contains the 27 lottery pairs used for inducing the progressive loss and gain ratios. The EV for each pair of bets is the same.

Table D.18: EVs and gain and loss ratios of the lotteries in Experiment 1: Magnitude effects in PR.

			Ratio					Ratio	
No.	Lottery	EV	Loss	Gain	No.	Lottery	EV	Loss	Gain
1	(9/12, 35; 3/12, -25) (3/12, 155; 9/12, -25)	20.0	-1.0	4.4	2	(9/12, 60; 3/12, -60) (3/12, 300; 9/12, -60)	30.0	-1.0	5.0
3	(9/12, 80; 3/12, -100) (3/12, 440; 9/12, -100)	35.0	-1.0	5.5	4	(9/12, 120; 3/12, -10) (3/12, 395; 9/12, -15)	87.5	-1.5	3.3
5	(9/12, 20; 3/12, -30) (3/12, 165; 9/12, -45)	7.5	-1.5	8.3	6	(9/12, 45; 3/12, -70) (3/12, 380; 9/12, -105)	16.3	-1.5	8.4
7	(9/12, 25; 3/12, -20) (3/12, 175; 9/12, -40)	13.8	-2.0	7.0	8	(9/12, 50; 3/12, -35) (3/12, 325; 9/12, -70)	28.8	-2.0	6.5
9	(9/12, 40; 3/12, -55) (3/12, 395; 9/12, -110)	16.3	-2.0	9.9	10	(9/12, 18; 3/12, -8) (3/12, 106; 9/12, -20)	11.5	-2.5	5.9
11	(9/12, 29; 3/12, -22) (3/12, 230; 9/12, -55)	16.3	-2.5	7.9	12	(9/12, 38; 3/12, -50) (3/12, 439; 9/12, -125)	16.0	-2.5	11.6
13	(9/12, 15; 3/12, -16) (3/12, 173; 9/12, -48)	7.3	-3.0	11.5	14	(9/12, 34; 3/12, -26) (3/12, 310; 9/12, -78)	19.0	-3.0	9.1
15	(9/12, 56; 3/12, -75) (3/12, 768; 9/12, -225)	23.3	-3.0	13.7	16	(9/12, 16; 3/12, -21) (3/12, 279; 9/12, -84)	6.8	-4.0	17.4

Table D.18: EVs and gain and loss ratios of the lotteries in Experiment 1: Magnitude effects in PR. (continued)

			Ratio					Ratio	
No.	Lottery	EV	Loss	Gain	No.	Lottery	EV	Loss	Gain
17	(9/12, 22; 3/12, -45) (3/12, 561; 9/12, -180)	5.3	-4.0	25.5	18	(9/12, 80; 3/12, -10) (3/12, 350; 9/12, -40)	57.5	-4.0	4.4
19	(9/12, 28; 3/12, -9) (3/12, 291; 9/12, -72)	18.8	-8.0	10.4	20	(9/12, 42; 3/12, -40) (3/12, 1,046; 9/12, -320)	21.5	-8.0	24.9
21	(9/12, 50; 3/12, -100) (3/12, 2,450; 9/12, -800)	12.5	-8.0	49.0	22	(9/12, 23; 3/12, -38) (3/12, 1,513; 9/12, -494)	7.8	-13.0	65.8
23	(9/12, 29; 3/12, -18) (3/12, 771; 9/12, -234)	17.3	-13.0	26.6	24	(9/12, 70; 3/12, -100) (3/12, 4,010; 9/12, -1,300)	27.5	-13.0	57.3
25	(9/12, 30; 3/12, -42) (3/12, 1,938; 9/12, -630)	12.0	-15.0	64.6	26	(9/12, 46; 3/12, -28) (3/12, 1,370; 9/12, -420)	27.5	-15.0	29.8
27	(9/12, 100; 3/12, -10) (3/12, 740; 9/12, -150)	72.5	-15.0	7.4					

Appendix D.3. Experiment 2: Binary choices in PR

Table D.19 contains the 50 lottery pairs being constrained by the prerequisites of propositions and conjectures. The EV for each pair of bets is the same.

Table D.19: EVs and gain and loss ratios of the lotteries in Experiment 2: Binary choices in PR.[a]

			Ratio					Ratio	
No.	Lottery	EV	Loss	Gain	No.	Lottery	EV	Loss	Gain
Proposition 1.1: $(\exists\ v_{\mathrm{P}}^{+} = v_{\$}^{+},\ v_{\mathrm{P}}^{+} > v_{\$}^{-},\ v_{\$}^{-} > v_{\mathrm{P}}^{-},\ p_{\mathrm{P}} - p_{\$} > 1 - p_{\mathrm{P}})\ v_{\$}^{-} - v_{\mathrm{P}}^{-} > v_{\mathrm{P}}^{+} - v_{\$}^{-}$									
1	(75%, 10; 25%, -23) (25%, 10; 75%, -1)	1.75	-23.0	1.0	2	(75%, 15; 25%, -39) (25%, 15; 75%, -3)	1.50	-13.0	1.0
3	(75%, 20; 25%, -46) (25%, 20; 75%, -2)	3.50	-23.0	1.0	4	(75%, 25; 25%, -62) (25%, 25; 75%, -4)	3.25	-15.5	1.0
Proposition 1.2: $(\exists\ v_{\mathrm{P}}^{+} = v_{\$}^{+},\ v_{\mathrm{P}}^{+} > v_{\$}^{-},\ v_{\$}^{-} > v_{\mathrm{P}}^{-},\ 1 - p_{\mathrm{P}} > p_{\mathrm{P}} - p_{\$})\ v_{\mathrm{P}}^{+} - v_{\$}^{-} > v_{\$}^{-} - v_{\mathrm{P}}^{-}$									
5	(60%, 5; 40%, -7) (40%, 5; 60%, -3)	0.20	-2.3	1.0	6	(60%, 10; 40%, -11) (40%, 10; 60%, -4)	1.60	-2.8	1.0
7	(60%, 15; 40%, -9) (40%, 15; 60%, -1)	5.40	-9.0	1.0	8	(60%, 20; 40%, -13) (40%, 20; 60%, -2)	6.80	-6.5	1.0
Proposition 3.1: $(\exists\ v_{\$}^{+} > v_{\mathrm{P}}^{+},\ v_{\mathrm{P}}^{+} > v_{\$}^{-},\ v_{\mathrm{P}}^{-} = v_{\$}^{-},\ p_{\$} > p_{\mathrm{P}} - p_{\$})\ v_{\mathrm{P}}^{+} - v_{\$}^{-} > v_{\$}^{+} - v_{\mathrm{P}}^{+}$									
9	(60%, 5; 40%, -3) (40%, 9; 60%, -3)	1.80	-1.0	1.8	10	(60%, 10; 40%, -4) (40%, 17; 60%, -4)	4.40	-1.0	1.7
11	(60%, 15; 40%, -19) (40%, 32; 60%, -19)	1.40	-1.0	2.1	12	(60%, 20; 40%, -26) (40%, 43; 60%, -26)	1.60	-1.0	2.2
Proposition 3.2: $(\exists\ v_{\$}^{+} > v_{\mathrm{P}}^{+},\ v_{\mathrm{P}}^{+} > v_{\$}^{-},\ v_{\mathrm{P}}^{-} = v_{\$}^{-},\ p_{\mathrm{P}} - p_{\$} > p_{\$})\ v_{\$}^{+} - v_{\mathrm{P}}^{+} > v_{\mathrm{P}}^{+} - v_{\$}^{-}$									
13	(75%, 5; 25%, -5) (25%, 25; 75%, -5)	2.50	-1.0	5.0	14	(75%, 10; 25%, -3) (25%, 36; 75%, -3)	6.75	-1.0	3.6
15	(75%, 15; 25%, -12) (25%, 71; 75%, -12)	8.75	-1.0	4.7	16	(75%, 20; 25%, -10) (25%, 80; 75%, -10)	12.50	-1.0	4.0

Table D.19: EVs and gain and loss ratios of the lotteries in Experiment 2: Binary choices in PR.[a] (continued)

			Ratio					Ratio	
No.	Lottery	EV	Loss	Gain	No.	Lottery	EV	Loss	Gain
	Conjecture 4.1: $(\exists\ v^{+}_{\$} > v^{+}_{P},\ v^{+}_{P} > v^{-}_{\$},\ v^{-}_{\$} > v^{-}_{P})\ v^{+}_{\$} - v^{+}_{P} > v^{+}_{P} - v^{-}_{\$}$ and $v^{+}_{\$} - v^{+}_{P} > v^{-}_{\$} - v^{-}_{P}$								
17	(75%, 5; 25%, -4) (25%, 17; 75%, -2)	2.75	-2.0	3.4	18	(75%, 10; 25%, -6) (25%, 39; 75%, -5)	6.00	-1.2	3.9
19	(75%, 15; 25%, -10) (25%, 38; 75%, -1)	8.75	-10.0	2.5	20	(75%, 20; 25%, -18) (25%, 51; 75%, -3)	10.50	-6.0	2.6
21	(75%, 25; 25%, -32) (25%, 55; 75%, -4)	10.75	-8.0	2.2	22	(75%, 30; 25%, -24) (25%, 84; 75%, -6)	16.50	-4.0	2.8
	Conjecture 4.2: $(\exists\ v^{+}_{\$} > v^{+}_{P},\ v^{+}_{P} > v^{-}_{\$},\ v^{-}_{\$} > v^{-}_{P})\ v^{+}_{P} - v^{-}_{\$} > v^{+}_{\$} - v^{+}_{P}$ and $v^{+}_{P} - v^{-}_{\$} > v^{-}_{\$} - v^{-}_{P}$								
23	(60%, 5; 40%, -6) (40%, 9; 60%, -5)	0.60	-1.2	1.8	24	(60%, 10; 40%, -8) (40%, 13; 60%, -4)	2.80	-2.0	1.3
25	(60%, 16; 40%, -8) (40%, 19; 60%, -2)	6.40	-4.0	1.2	26	(60%, 21; 40%, -8) (40%, 25; 60%, -1)	9.40	-8.0	1.2
27	(60%, 30; 40%, -18) (40%, 34; 60%, -3)	11.80	-6.0	1.1	28	(60%, 110; 40%, -60) (40%, 114; 60%, -6)	42.00	-10.0	1.0
	Conjecture 5.1: $(\exists\ v^{+}_{\$} > v^{+}_{P},\ v^{+}_{P} > v^{-}_{\$},\ v^{-}_{P} > v^{-}_{\$})\ v^{+}_{\$} - v^{+}_{P} > v^{+}_{P} - v^{-}_{\$}$ and $v^{+}_{\$} - v^{+}_{P} > v^{-}_{P} - v^{-}_{\$}$								
29	(75%, 5; 25%, -3) (25%, 30; 75%, -6)	3.00	-2.0	6.0	30	(75%, 10; 25%, -2) (25%, 52; 75%, -8)	7.00	-4.0	5.2
31	(75%, 15; 25%, -6) (25%, 183; 75%, -48)	9.75	-8.0	12.2	32	(75%, 20; 25%, -4) (25%, 124; 75%, -24)	13.00	-6.0	6.2
33	(75%, 25; 25%, -1) (25%, 104; 75%, -10)	18.50	-10.0	4.2	34	(75%, 30; 25%, -5) (25%, 103; 75%, -6)	21.25	-1.2	3.4

Table D.19: EVs and gain and loss ratios of the lotteries in Experiment 2: Binary choices in PR.[a] (continued)

			Ratio					Ratio	
No.	Lottery	EV	Loss	Gain	No.	Lottery	EV	Loss	Gain
Conjecture 5.2: $(\exists\ v_{\$}^{+} > v_{\mathrm{P}}^{+},\ v_{\mathrm{P}}^{+} > v_{\$}^{-},\ v_{\mathrm{P}}^{-} > v_{\$}^{-})\ v_{\mathrm{P}}^{+} - v_{\$}^{-} > v_{\$}^{+} - v_{\mathrm{P}}^{+}$ and $v_{\mathrm{P}}^{+} - v_{\$}^{-} > v_{\mathrm{P}}^{-} - v_{\$}^{-}$									
35	(60%, 6; 40%, -5) (40%, 13; 60%, -6)	1.60	-1.2	2.2	36	(60%, 10; 40%, -3) (40%, 30; 60%, -12)	4.80	-4.0	3.0
37	(60%, 16; 40%, -4) (40%, 32; 60%, -8)	8.00	-2.0	2.0	38	(60%, 20; 40%, -2) (40%, 52; 60%, -16)	11.20	-8.0	2.6
39	(60%, 26; 40%, -6) (40%, 87; 60%, -36)	13.20	-6.0	3.4	40	(60%, 30; 40%, -1) (40%, 59; 60%, -10)	17.60	-10.0	2.0
Conjecture 6.2: $(\exists\ v_{\mathrm{P}}^{+} > v_{\$}^{+},\ v_{\mathrm{P}}^{+} > v_{\$}^{-},\ v_{\$}^{-} > v_{\mathrm{P}}^{-})\ v_{\mathrm{P}}^{+} - v_{\$}^{-} > v_{\mathrm{P}}^{+} - v_{\$}^{+}$ and $v_{\mathrm{P}}^{+} - v_{\$}^{-} > v_{\$}^{-} - v_{\mathrm{P}}^{-}$									
41	(60%, 6; 40%, -8) (40%, 4; 60%, -2)	0.40	-4.0	1.5	42	(60%, 15; 40%, -18) (40%, 9; 60%, -3)	1.80	-6.0	1.7
43	(60%, 28; 40%, -32) (40%, 16; 60%, -4)	4.00	-8.0	1.8	44	(60%, 41; 40%, -50) (40%, 19; 60%, -5)	4.60	-10.0	2.2
Conjecture 6.3: $(\exists\ v_{\mathrm{P}}^{+} > v_{\$}^{+},\ v_{\mathrm{P}}^{+} > v_{\$}^{-},\ v_{\$}^{-} > v_{\mathrm{P}}^{-})\ v_{\$}^{-} - v_{\mathrm{P}}^{-} > v_{\mathrm{P}}^{+} - v_{\$}^{+}$ and $v_{\$}^{-} - v_{\mathrm{P}}^{-} > v_{\mathrm{P}}^{+} - v_{\$}^{-}$									
45	(75%, 20; 25%, -58) (25%, 5; 75%, -1)	0.50	-58.0	4.0	46	(75%, 11; 25%, -29) (25%, 10; 75%, -2)	1.00	-14.5	1.1
47	(75%, 120; 25%, -354) (25%, 15; 75%, -3)	1.50	-118.0	8.0	48	(75%, 240; 25%, -712) (25%, 20; 75%, -4)	2.00	-178.0	12.0
49	(75%, 150; 25%, -440) (25%, 25; 75%, -5)	2.50	-88.0	6.0	50	(75%, 300; 25%, -888) (25%, 30; 75%, -6)	3.00	-148.0	10.0

[a] P-bet = $(p_{\mathrm{P}},\ v_{\mathrm{P}}^{+};\ 1 - p_{\mathrm{P}},\ v_{\mathrm{P}}^{-})$ and \$-bet = $(p_{\$},\ v_{\$}^{+};\ 1 - p_{\$},\ v_{\$}^{-})$, where, by definition, $(\forall\ p_{\mathrm{P}},\ p_{\$},\ v_{\mathrm{P}}^{+},\ v_{\mathrm{P}}^{-},\ v_{\$}^{+},\ v_{\$}^{-} \in \mathbb{R})\ (\exists\ 1 > p_{\mathrm{P}} > p_{\$} > 0,\ v_{\mathrm{P}}^{+},\ v_{\$}^{+} > 0 > v_{\mathrm{P}}^{-},\ v_{\$}^{-})\ p_{\mathrm{P}} v_{\mathrm{P}}^{+} + (1 - p_{\mathrm{P}}) v_{\mathrm{P}}^{-} = p_{\$} v_{\$}^{+} + (1 - p_{\$}) v_{\$}^{-}$—that is, the EVs of the P-bet and \$-bet in a given lottery are equivalent. As outlined in Section 2.2, for simplicity, we define the relations between the payoffs v_{P}^{+} and $v_{\$}^{+}$ and between the payoffs v_{P}^{-} and $v_{\$}^{-}$ more generally in the current experiment, namely $v_{\mathrm{P}}^{+},\ v_{\$}^{+} > 0 > v_{\mathrm{P}}^{-},\ v_{\$}^{-}$ instead of $v_{\$}^{+} > v_{\mathrm{P}}^{+} > 0 > v_{\mathrm{P}}^{-} > v_{\$}^{-}$.

Appendix D.4. Experiment 3: Episodic memory in PR

Table D.20 contains the 2 lottery pairs of fillers, the 22 lottery pairs of targets, and the 22 lottery pairs of distractors used for yielding the different EVs *between* bet pairs and for the memory test. The EV for each pair of bets is the same.

Table D.20: Products, images, MSRPs, EVs, and loss and gain ratios of paired “P-bet” and “$-bet” options: Fillers, targets, and distractors.

						Ratios[d]								Ratios[d]	
No.	Products[a]	Images	MSRPs[b]	Options[c]	EVs	Losses	Gains	No.	Products[a]	Images	MSRPs[b]	Options[c]	EVs	Losses	Gains
2 filler pairs:															
1	Helio cereals honey candy		3.5	(70%, 2; 30%, -2)	2.8	-5.0	13.0	2	Swarovski symbolic bracelet		375.0	(75%, 3; 25%, -1)	750.0	-5.0	7.7
				(30%, 26; 70%, -10)								(25%, 23; 75%, -5)			
22 target pairs and their corresponding 22 distractor pairs:															
3	Italian blanket and bed		425.0	(70%, 2; 30%, -1)	467.5	-1.0	3.0	4	Philips coffer machine		1450.0	(75%, 3; 25%, -2)	2537.5	-1.0	4.3
				(30%, 6; 70%, -1)								(25%, 13; 75%, -2)			
				(85%, 2; 15%, -1)	658.8							(85%, 3; 15%, -2)	3262.5		
				(15%, 6; 85%, -1)	21.3							(15%, 13; 85%, -2)	362.5		
5	Vitarol marinated mushroom		4.0	(85%, 2; 15%, -1)	6.2	-1.0	8.0	6	Super Zings cyber squad set		30.0	(70%, 2; 30%, -2)	24.0	-2.0	6.0
				(15%, 16; 85%, -1)								(30%, 12; 70%, -4)			
				(30%, 16; 70%, -1)	16.4							(80%, 2; 20%, -2)	36.0		
				(70%, 2; 30%, -1)	4.4							(15%, 12; 85%, -4)	-48.0		
7	Książęce black beer		3.8	(80%, 3; 20%, -1)	8.4	-2.0	6.3	8	LG LKB television		1250.0	(85%, 2; 15%, -2)	1750.0	-2.0	16.0
				(20%, 19; 80%, -2)								(15%, 32; 85%, -4)			
				(70%, 3; 30%, -1)	6.8							(30%, 32; 70%, -4)	8250.0		
				(85%, 3; 15%, -1)	8.6							(75%, 2; 25%, -2)	1250.0		

Table D.20: Products, images, MSRPs, EVs, and loss and gain ratios of paired “P-bet” and “$-bet” options: Fillers, targets, and distractors. (continued)

						Ratios[d]								Ratios[d]	
No.	Products[a]	Images	MSRPs[b]	Options[c]	EVs	Losses	Gains	No.	Products[a]	Images	MSRPs[b]	Options[c]	EVs	Losses	Gains
9	Marmalade donuts		3.6	(70%, 3; 30%, -1)	6.5	-3.0	4.3	10	Massimo Giacon “Halloween” cap		33.0	(75%, 2; 25%, -2)	33.0	-3.0	11.0
				(30%, 13; 70%, -3)								(25%, 22; 75%, -6)			
				(20%, 13; 80%, -3)	0.7							(80%, 2; 20%, -2)	39.6		
				(85%, 3; 15%, -1)	8.6							(20%, 22; 80%, -6)	39.6		
11	Unity Varsovia bicycle		1300.0	(80%, 2; 20%, -1)	1820.0	-3.0	9.5	12	Dyson vacuum cleaner		370.0	(85%, 3; 15%, -2)	832.5	-3.0	16.3
				(20%, 19; 80%, -3)								(15%, 49; 85%, -6)			
				(70%, 2; 30%, -1)	1430.0							(25%, 49; 75%, -6)	2867.5		
				(30%, 19; 70%, -3)	4680.0							(70%, 3; 30%, -2)	555.0		
13	Prymat grill		3.0	(75%, 3; 25%, -2)	5.3	-4.0	10.3	14	Beko microwave		600.0	(80%, 3; 20%, -2)	1200.0	-4.0	14.0
				(25%, 31; 75%, -8)								(20%, 42; 80%, -8)			
				(85%, 3; 15%, -2)	6.8							(70%, 3; 30%, -2)	900.0		
				(30%, 31; 70%, -8)	11.1							(25%, 42; 75%, -8)	2700.0		
15	Parker jotter pen		35.0	(85%, 2; 15%, -1)	54.3	-4.0	16.5	16	Philips steam generator		430.0	(70%, 3; 30%, -1)	774.0	-6.0	6.7
				(15%, 33; 85%, -4)								(30%, 20; 70%, -6)			
				(75%, 2; 25%, -1)	43.8							(85%, 3; 15%, -1)	1032.0		
				(30%, 33; 70%, -4)	248.5							(25%, 20; 75%, -6)	215.0		

Table D.20: Products, images, MSRPs, EVs, and loss and gain ratios of paired “P-bet” and “\$-bet” options: Fillers, targets, and distractors. (continued)

						Ratios[d]								Ratios[d]	
No.	Products[a]	Images	MSRPs[b]	Options[c]	EVs	Losses	Gains	No.	Products[a]	Images	MSRPs[b]	Options[c]	EVs	Losses	Gains
17	Vespa motorcycle		1550.0	(75%, 2; 25%, -2)	1550.0	-6.0	20.0	18	Unbranded air moisturizer		38.0	(80%, 2; 20%, -2)	45.6	-6.0	27.0
				(25%, 40; 75%, -12)								(20%, 54; 80%, -12)			
				(80%, 2; 20%, -2)	1860.0							(85%, 2; 15%, -2)	45.6		
				(30%, 40; 70%, -12)	5580.0							(25%, 54; 75%, -12)	171.0		
19	Frozen honey cake		3.5	(85%, 3; 15%, -1)	8.4	-6.0	16.7	20	Honor smart touch watch		36.0	(70%, 2; 30%, -2)	28.8	-8.0	20.0
				(15%, 50; 85%, -6)								(30%, 40; 70%, -16)			
				(80%, 3; 20%, -1)	7.7							(85%, 2; 15%, -2)	50.4		
				(30%, 50; 70%, -6)	41.3							(25%, 40; 75%, -16)	-72.0		
21	HP laptop		1600.0	(85%, 2; 15%, -2)	2240.0	-8.0	50.0	22	Electric toothbrush		48.0	(75%, 3; 25%, -2)	84.0	-10.0	22.3
				(15%, 100; 85%, -16)								(25%, 67; 75%, -20)			
				(80%, 2; 20%, -2)	1920.0							(85%, 3; 15%, -2)	108.0		
				(30%, 100; 70%, -16)	30080.0							(15%, 67; 85%, -20)	-333.6		
23	Tissot automatic watch		1400.0	(80%, 3; 20%, -2)	2800.0	-10.0	30.0	24	Nike Jordan Air 1 Retro High		400.0	(85%, 2; 15%, -1)	620.0	-10.0	33.5
				(20%, 90; 80%, -20)								(15%, 67; 85%, -10)			
				(75%, 3; 25%, -2)	2450.0							(75%, 2; 25%, -1)	500.0		
				(30%, 90; 70%, -20)	18200.0							(30%, 67; 70%, -10)	5240.0		

[a] The descriptions of the products are not shown to the participants.

[b] MSRPs denote the manufacturer’s suggested retail prices (PLN) per single product.

[c] Among the affiliated four options of each product, the upper and lower two represent the targets and their distractors, respectively.

[d] The loss and gain ratios are calculated by means of the amounts of loss and gain of the “\$-bet” option divided by the amounts of loss and gain of the “P-bet” option, respectively, and their results are rounded off to one decimal place.

Appendix D.5. Experiment 4: Episodic memory in attraction effect PR

Table D.21, Table D.22, and Table D.23 contain the target, attraction decoy, buffer, and distractor bets (cf., Figure D.23) used for yielding the different EVs *within* the P-bet and $-bet in a given bet pair and for the memory test.

Table D.21: EVDs of lotteries and words: Targets, competitors, attraction decoys, and buffers.[a]

				Words						Words	
No.	Lottery	EVs	EVDs	Targets	Decoys	No.	Lottery	EVs	EVDs	Targets	Decoys
				Targets, competitors, and decoys:							
	(70%, 23; 30%, -17)	11.0	0%	kadłub			(70%, 37; 30%, -18)	20.5	0%	płaszcz	
1	(25%, 68; 75%, -8)			ciocia		2	(35%, 79; 65%, -11)			łańcuch	
	(60%, 23; 40%, -17)	7.0			znajomy		(30%, 79; 70%, -11)	16.0			malarz
	(75%, 35; 25%, -49)	14.0	0%	tablica			(75%, 40; 25%, -32)	22.0	0%	gromada	
3	(25%, 92; 75%, -12)			górnik		4	(40%, 70; 60%, -10)			twórca	
	(64%, 35; 36%, -49)	4.8			kodeks		(34%, 70; 66%, -10)	17.2			odznaka
	(80%, 25; 20%, -20)	16.0	0%	ubranie			(80%, 32; 20%, -45)	16.6	0%	gardło	
5	(30%, 65; 70%, -5)			kolejka		6	(30%, 81; 70%, -11)			wejście	
	(68%, 25; 32%, -20)	10.6			grzbiet		(26%, 81; 74%, -11)	12.9			ścieżka
	(85%, 17; 15%, -9)	13.1	0%	klient			(85%, 24; 15%, -66)	10.5	0%	ziarno	
7	(30%, 67; 70%, -10)			dźwięk		8	(25%, 66; 75%, -8)			oparcie	
	(72%, 17; 28%, -9)	9.7			zegarek		(21%, 66; 79%, -8)	7.5			kolumna
	(70%, 29; 30%, -17)	15.2	(↓) 50%	koncert			(75%, 30; 25%, -18)	18.0	(↓) 50%	krzesło	
9	(40%, 75; 60%, -12)	22.8		dworzec		10	(35%, 92; 65%, -8)	27.0		styczeń	
	(60%, 29; 40%, -17)	10.6			siatka		(30%, 92; 70%, -8)	22.0			powieść
	(80%, 16; 20%, -9)	11.0	(↓) 50%	więzień			(85%, 22; 15%, -14)	16.6	(↓) 50%	kartka	
11	(25%, 75; 75%, -3)	16.5		egzamin		12	(30%, 90; 70%, -3)	24.9		północ	
	(68%, 16; 32%, -9)	8.0			silnik		(26%, 90; 74%, -3)	21.2			jezioro
	(70%, 27; 30%, -19)	13.2	(↑) 50%	drewno			(75%, 35; 25%, -15)	22.5	(↑) 50%	przewód	
13	(30%, 48; 70%, -8)	8.8		kuchnia		14	(40%, 48; 60%, -7)	15.0		magazyn	
	(60%, 27; 40%, -19)	8.6			chodnik		(34%, 48; 66%, -7)	11.7			komora

Table D.21: EVDs of lotteries and words: Targets, competitors, attraction decoys, and buffers.[a] (continued)

				Words						Words	
No.	Lottery	EVs	EVDs	Targets	Decoys	No.	Lottery	EVs	EVDs	Targets	Decoys
	(80%, 31; 20%, -19)	21.0	(↑) 50%	stolik			(85%, 27; 15%, -35)	17.7	(↑) 50%	biurko	
15	(25%, 74; 75%, -6)	14.0		bohater		16	(30%, 65; 70%, -11)	11.8		centrum	
	(68%, 31; 32%, -19)	15.0			wakacje		(26%, 65; 74%, -11)	8.8			hrabia
	(70%, 20; 30%, -3)	13.1	(↓) 100%	autobus			(75%, 32; 25%, -52)	11.0	(↓) 100%	spodnie	
17	(40%, 79; 60%, -9)	26.2		pacjent		18	(30%, 85; 70%, -5)	22.0		żołądek	
	(60%, 20; 40%, -3)	10.8			tęsknić		(26%, 85; 74%, -5)	18.4			wysiłek
	(80%, 20; 20%, -40)	8.0	(↓) 100%	randka			(85%, 18; 15%, -46)	8.4	(↓) 100%	prezent	
19	(35%, 81; 65%, -19)	16.0		handel		20	(30%, 70; 70%, -6)	16.8		ofiara	
	(68%, 20; 32%, -40)	0.8			strzał		(26%, 70; 74%, -6)	13.8			koniec
	(70%, 30; 30%, -42)	8.4	(↑) 100%	interes			(75%, 38; 25%, -66)	12.0	(↑) 100%	granica	
21	(35%, 38; 65%, -14)	4.2		smutek		22	(20%, 70; 80%, -10)	6.0		choroba	
	(60%, 30; 40%, -42)	1.2			królowa		(17%, 70; 83%, -10)	3.6			uśmiech
	(80%, 50; 20%, -30)	34.0	(↑) 100%	diabeł			(85%, 32; 15%, -64)	17.6	(↑) 100%	budynek	
23	(25%, 80; 75%, -4)	17.0		chmura		24	(30%, 76; 70%, -20)	8.8		teoria	
	(68%, 50; 32%, -30)	24.4			oddech		(26%, 76; 74%, -20)	5.0			wiosna
Buffers:											
	(70%, 30; 30%, -40)	9.0	(↑) 50%	reguła			(75%, 24; 25%, -8)	16.0	(↑) 100%	pokład	
25	(20%, 86; 80%, -14)	6.0		muzyka		26	(20%, 60; 80%, -5)	8.0		szczyt	
	(60%, 30; 40%, -40)	2.0			gwiazda		(17%, 60; 83%, -5)	6.1			wiersz
	(80%, 21; 20%, -24)	12.0	0%	rodzice			(85%, 16; 15%, -8)	12.4	0%	zwyczaj	
27	(30%, 68; 70%, -12)			mistrz		28	(30%, 74; 70%, -14)			wygląd	
	(68%, 21; 32%, -24)	6.6			statek		(26%, 74; 74%, -14)	8.9			święto

[a] Only the underlined words and their corresponding lotteries were included in the memory test. See Table D.23 for the English meanings of the Polish words.

Table D.22: The lotteries and words: Distractors.[a]

No.	Lottery	EVs	Distractors	No.	Lottery	EVs	Distractors
			Distractors:				
29	(75%, 30; 25%, -20)	17.5	pawilon	30	(25%, 27; 75%, -7)	1.5	gabinet
31	(30%, 82; 70%, -28)	5.0	depesza	32	(80%, 35; 20%, -18)	24.4	białko
33	(72%, 36; 28%, -19)	20.6	ogniwo	34	(28%, 84; 72%, -21)	12.9	tramwaj
35	(78%, 22; 22%, -23)	12.1	hodowla	36	(27%, 76; 73%, -24)	3.0	schemat
37	(85%, 19; 15%, -21)	13.0	podłoga	38	(20%, 86; 80%, -8)	10.8	butelka
39	(66%, 24; 34%, -11)	12.1	zapach	40	(28%, 89; 72%, -6)	20.6	rysunek
41	(70%, 38; 30%, -17)	21.5	pojazd	42	(35%, 77; 65%, -13)	18.5	siostra
43	(72%, 33; 28%, -17)	19.0	dziadek	44	(28%, 72; 72%, -18)	7.2	szpital
45	(75%, 19; 25%, -9)	12.0	maszyna	46	(35%, 71; 65%, -17)	13.8	piasek
47	(66%, 22; 34%, -13)	10.1	oddział	48	(29%, 75; 71%, -15)	11.1	gwiazda
49	(80%, 23; 20%, -37)	11.0	poziom	50	(25%, 80; 75%, -18)	6.5	pomyłka
51	(74%, 42; 26%, -28)	23.8	godzina	52	(28%, 74; 72%, -21)	5.6	cesarz

[a] *Note*: As per Table D.21.

Table D.23: Full list of word stimuli: Targets, decoys, distractors, and buffers.[a]

48 targets		28 decoys	28 distractors	12 buffers
kadłub (hull)	ciocia (aunt)	znajomy (friend)	pawilon (pavilion)	reguła (rule)
płaszcz (coat)	łańcuch (chain)	malarz (painter)	gabinet (cabinet)	muzyka (music)
tablica (blackboard)	górnik (miner)	kodeks (code)	depesza (telegram)	gwiazda (star)
gromada (flock)	twórca (creator)	odznaka (badge)	białko (protein)	pokład (deck)
ubranie (cloth)	kolejka (queue)	grzbiet (edge)	ogniwo (link)	szczyt (peak)
gardło (throat)	wejście (entrance)	ścieżka (path)	tramwaj (tram)	wiersz (poem)
klient (client)	dźwięk (sound)	zegarek (watch)	hodowla (breeding)	rodzice (parents)
ziarno (grain)	oparcie (backrest)	kolumna (column)	schemat (scheme)	mistrz (master)
koncert (concert)	dworzec (station)	siatka (grid)	podłoga (floor)	statek (ship)
krzesło (chair)	styczeń (January)	powieść (novel)	butelka (bottle)	zwyczaj (custom)
więzień (prisoner)	egzamin (exam)	silnik (engine)	zapach (smell)	wygląd (appearance)
kartka (card)	północ (midnight)	jezioro (lake)	rysunek (drawing)	święto (feast)
drewno (wood)	kuchnia (kitchen)	chodnik (pavement)	pojazd (vehicle)	
przewód (wire)	magazyn (magazine)	komora (chamber)	siostra (sister)	
stolik (board)	bohater (hero)	wakacje (holiday)	dziadek (grandfather)	
biurko (desk)	centrum (hub)	hrabia (count)	szpital (hospital)	
autobus (bus)	pacjent (patient)	tęsknić (Miss)	maszyna (machine)	
spodnie (pants)	żołądek (stomach)	wysiłek (effort)	piasek (sand)	
randka (date)	handel (trade)	strzał (shot)	oddział (branch)	
prezent (gift)	ofiara (victim)	koniec (end)	gwiazda (star)	
interes (business)	smutek (sadness)	królowa (queen)	poziom (level)	
granica (border)	choroba (sickness)	uśmiech (grin)	pomyłka (blunder)	
diabeł (devil)	chmura (cloud)	oddech (breath)	godzina (hour)	
budynek (building)	teoria (theory)	wiosna (spring)	cesarz (emperor)	

[a] All the words are concrete nouns in Polish, with a mean frequency of 31.5 (range 22–51) occurrences per 0.5 million according to Kurcz, Lewicki, Sambor, Szafran and Woronczak (1990); besides, the words are six to seven letters in length, and have no obvious associations with the color green, blue, or red. The English meanings of Polish words are in parentheses.

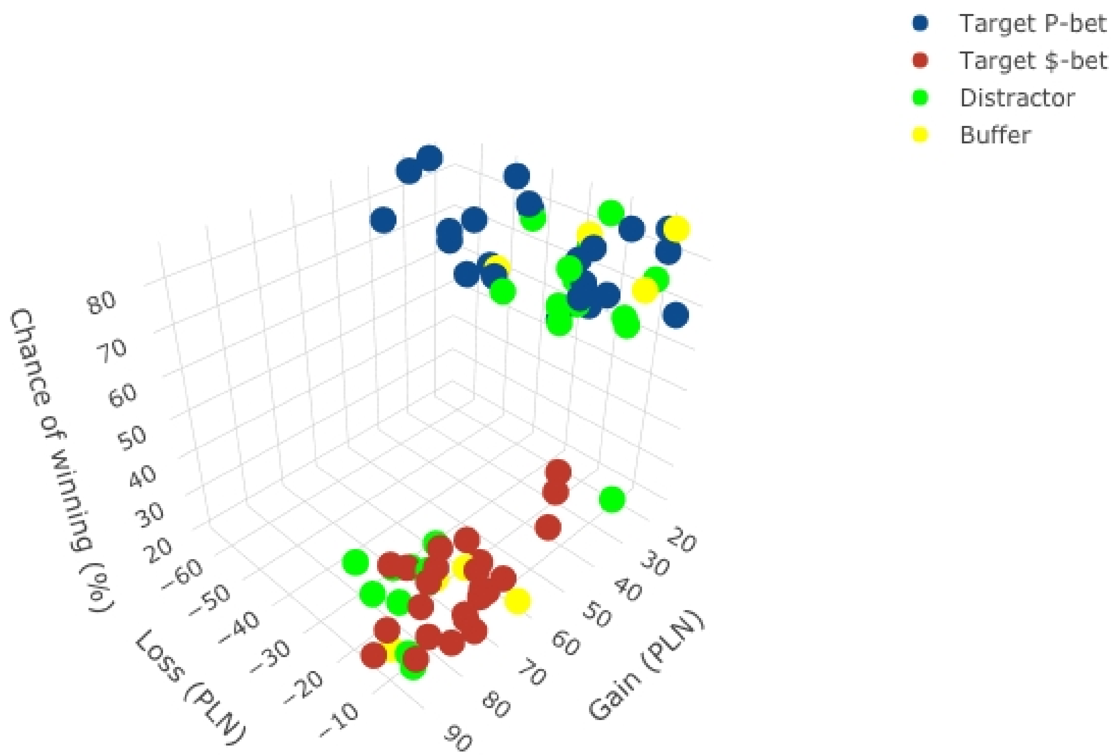


Figure D.23: Target P-bets and $-bets, distractors, and buffers.
Note: All the bets (dots) were represented in terms of their gain and loss payoffs (horizontal axes) and winning probabilities (vertical axis).

Appendix E. Instructions and material illustrations (English translation)

Appendix E.1. Experiment 1: Magnitude effects in PR[6]

Age: _____

Gender: _____

In the following two tasks, we ask you to think about a series of bets, for which you image that you can win or lose a certain amount of money with some probabilities. Specifically, in the first task, please choose one between two options in each question, and answer each question regardless of the other questions. In the second task, please specify a maximum amount that you would be willing to pay for participating in each bet, and enter this amount in the blank underline (all payoffs are in the Polish Złoty).

Task 1:

Question 1: Choose one that you prefer from the two bets:

_____ Bet A: Win 20 zł with a probability of 9/12, and lose 30 zł with a probability of 3/12.

_____ Bet B: Win 165 zł with a probability of 3/12, and lose 45 zł with a probability of 9/12.

Question 2: Choose one that you prefer from the two bets:

_____ Bet A: Win 45 zł with a probability of 9/12, and lose 70 zł with a probability of 3/12.

[6] It is noteworthy that the three different groups of samples (i.e., the 41, 39, and 57 participants) faced the different lotteries being exclusively assigned to each group, although the same instruction was present to all the 137 participants. The lottery examples presented here illustrate the paired bets nos. 5, 6 and 12 (cf., Table D.18) and were randomized as Question 1, Question 2, and the last Question 12, respectively, in a given leaflet exclusively to the group of the 41 participants.

_____ Bet B: Win 380 zł with a probability of 3/12, and lose 105 zł with a probability of 9/12.

......

Question 12: Choose one that you prefer from the two bets:

_____ Bet A: Win 38 zł with a probability of 9/12, and lose 50 zł with a probability of 3/12.

_____ Bet B: Win 439 zł with a probability of 3/12, and lose 125 zł with a probability of 9/12.

Task 2:

For each bet below, please enter a maximum amount you would be willing to pay to participate in the bet.

_____ Bet A: Win 20 zł with a probability of 9/12, and lose 30 zł with a probability of 3/12.

_____ Bet B: Win 165 zł with a probability of 3/12, and lose 45 zł with a probability of 9/12.

_____ Bet C: Win 45 zł with a probability of 9/12, and lose 70 zł with a probability of 3/12.

_____ Bet D: Win 380 zł with a probability of 3/12, and lose 105 zł with a probability of 9/12.

......

_____ Bet K: Win 38 zł with a probability of 9/12, and lose 50 zł with a probability of 3/12.

_____ Bet L: Win 439 zł with a probability of 3/12, and lose 125 zł with a probability of

9/12.

Appendix E.2. Experiment 2: Binary choices in PR

Age: ☐

Gender: Male ☐ Female ☐

Below is a series of paired bets presented for your choices, as if they were lotteries. Within each lottery pair, choose only one bet between Bet A and Bet B, so that it could be used for gambling. For each bet, it is composed of a probability (60% or 75%) of winning an amount of payoff and a probability (40% or 25%) of losing another amount of payoff. Please specify your preferred, favorite bet in each lottery pair by marking a "×" before the bet.

Pair 1:

☐ Bet A: 75% of winning 10 zł and 25% of losing 23 zł.

☐ Bet B: 25% of winning 10 zł and 75% of losing 1 zł.

Pair 2:

☐ Bet A: 75% of winning 15 zł and 25% of losing 39 zł.

☐ Bet B: 25% of winning 15 zł and 75% of losing 3 zł.

......

Pair 50:

☐ Bet A: 75% of winning 300 zł and 25% of losing 888 zł.

☐ Bet B: 25% of winning 30 zł and 75% of losing 6 zł.

Appendix E.3. Experiment 3: Episodic memory in PR

Appendix E.3.1. The general instruction given at the start of the experiment

At first, we will present to you a series of lottery pairs, then we will ask you to choose one lottery in each pair. Please, try to remember the one that you will choose and the one that you will reject in each pair, because we will ask you at the end to recollect these decisions.

Appendix E.3.2. The scenario informed to image within the choice task

Imagine that you are the owner of a large warehouse of goods cooperating with many stores from various industries. On the occasion of the 20^{th} anniversary of the Polish Society of Wholesale Sellers, a series of lotteries was organized, each of which has a specific chance of winning different goods from your warehouse, but there is also a specific risk that you will lose some goods. For example, a lottery might look like this:

— In the first bet you have 80% of winning two couches (each worth PLN 235) and 20% risk of losing one couch.

— While in the second bet you have a 20% chance of winning 30 couches and an 80% risk of losing 7 couches.

(Wins or losses can be converted into money instead of real items.)

Please choose only one lottery that you would like mostly in each pair.

Appendix E.3.3. The instruction given within the price task

Now imagine that your colleagues from another warehouse would like to take part in the lottery too, but they ran out of tickets. For each bet, please specify the amount you would be willing to sell to them. Below each bet, enter the amount in PLN you are willing to sell your stake, and press Enter to go to the next slide.

Appendix E.4. Experiment 4: Episodic memory in attraction effect PR

Appendix E.4.1. Participation invitation letter

Good morning Jan Kowalski (Invitee),

We would like to invite you to participate in an experiment involving decision making and memory recollection. The experiment will last for up to 1 hour and will be held fully at your own self-pace without in-person interactions with the research team. The experiment will not represent any psychological risks to you. The only disappointment you may face is not being remunerated for additional earnings. This is a study from the doctoral student Yong Lu and his supervisor Dr. Prof. Marek Nieznański, both at the Faculty of Christianity Philosophy, Cardinal Stefan Wyszyński University in Warsaw (UKSW).

Payments

- The amount of compensation for your participation will include 50 PLN for your "show up", and additional earnings will depend partly on your decisions and partly on chance.
- Payments to you will be made as online Empík e-card.

Rules

- You must be at least 18 years old.
- You must be able to speak Polish fluently.
- You must not make the question form received from the research team available on the internet or to third parties.
- You can participate through a computer or device with a larger screen than a smartphone and as long as you have the Adobe Reader or other such programs installed in it. No web camera or microphone are required.
- During the experiment, you must adhere to the rules laid down by the research team in the instructions.

Procedures

If you agree to participate in this experiment, you will be asked to fully complete:

- A basic demographic questionnaire that includes your age, gender, university and major if applicable, and email address that will take approximately one minute to complete.
- A choice and learning task that includes 26 questions that will take approximately 15 minutes to complete.
- A valuation task that includes 78 questions that will take approximately 25 minutes to complete.
- A memory recollection task that includes 72 questions that will take approximately 20 minutes to complete.

Privacy

- The identifying information such as your name and email address is only for the purpose of sending the experimental question form and paying reimbursement, and it will not be used for any purposes outside of this study. Other personal information, such as age, gender, and academic major, will be used as part of our ongoing research.
- The generated, anonymized data is used for the preparation of a scientific research paper and lectures. Your individual privacy will be maintained in all published and written data resulting from the experiment. The research team will treat all the data made by the participants anonymized and will not assign these data to any other institutions or persons. Participation in this experiment is anonymous in this sense.

Contacts and questions

If you have any questions now or at a later time, you may contact Yong Lu, via luyong@student.uksw.edu.pl. You can ask any questions you have before you begin the experiment.

Statement of consent

I have read the above information. I feel I understand the study well enough to make a decision about my participation. I understand and agree to the terms described above.

Participation

If you want to participate, please reply to this email for registration, by indicating your willingness to participate and agreeing to the statement of consent. You will receive email with a question form and a base remuneration attached after we sign you up for participation. You also have right to withdraw consent at any time in writing to inform a member of the study team. Thank you and we hope to see your participation soon!

One side experiment

We will be grateful if you can also complete another one side experiment involving making 50 choice decisions. We think they will take you about 10-15 minutes. Please note that these two experiments are ENTIRELY independent with each other.

Sincerely yours,

Yong Lu

Appendix E.4.2. Participation registration letter

Good morning Jan Kowalski (Invitee),

Thank you for your interest in participating in our experiments. Attached please find the two question forms that are independent with each other. Please, fill them out fully and then send back to luyong@student.uksw.edu.pl. We first reimburse you a 25 PLN online Empík e-card (no. xxxxxxxxxxx) due by 30 October 2021 (www.empik.com). Upon receiving your fully completed forms, we will reimburse you another 25 PLN.

Thanks in advance for your thoughtful completion of these questions — we really appreciate your time and effort. We look forward to receiving your answers.

Sincerely yours,

Yong Lu

Appendix E.4.3. Participation reception letter

Good morning Jan Kowalski (Invitee),

Thank you for sending back your completed form to us. Here is your another 25 PLN online Empík e-card (no. xxxxxxxxxxx) as the second part of your base remuneration.

The bet represented by the random number (i.e., xx) that you have played out for real is the one having a xx% probability of winning xx PLN and a xx% probability of losing xx PLN, as attached by the word "xxxxxxx". The offer price represented by another random number for the bet is x PLN. As seen, the amount of minimum selling price of the bet that you stated is less/equal to/greater than the offer price. According to the rules, your additional earnings are 0/25 PLN reimbursed by a 25 PLN online Empík e-card (no. xxxxxxxxxxx).

Sincerely yours,

Yong Lu

Appendix E.4.4. Question form

PLEASE READ THE FOLLOWING INSTRUCTIONS CAREFULLY BEFORE FILLING THE FORM

Experimental Instructions

Introduction

This is an experiment in decision making and memory. We think that the entire experiment will take you about 1 hour, including the time taken to read and understand the instructions. **Kindly please note that once you have started your answers, you are required to *not* take breaks.** You can save data typed into the form by clicking on the "save file" icon in the Adobe Reader or other such programs. If you have any questions after reading the instructions, please contact Yong Lu, via luyong@student.uksw.edu.pl. You can ask any questions you have before you begin answering the questions. **After you have done all the questions, please save your completed form to your local computer, and send as an attachment via email to Yong Lu.** Once you have submitted your form, you will *not* later be allowed to change any of them .

In the beginning of this form, you will be asked to complete a brief demographic questionnaire. Then, the rest questions come in three tasks. First, a set of 26 questions asking you to choose among three options in each question. Second, a set of 78 questions asking you to evaluate prices for the options. Third, another 72 memory questions. **Please note that the questions must be completed sequentially, that is, from the first page to the last page.** Details of how you will make decisions and judgments, receive additional earnings, and follow the rules will be provided below.

Task 1

In this task, you will participate in 26 independent decision problems that share a common form regarding bets. As indicated by Figure 1 for an example, each bet is composed of a certain amount of money to win or lose with some probabilities. More specifically, (1) each of the top, middle, and bottom rows contains 100 squares; (2) the numbers of green and white squares in the top row represent the probabilities (unit: %) of gain and loss payoffs of a bet, respectively; (3) the numbers of blue squares in the middle row represent the gain payoff of a bet; (4) the numbers of red squares in the bottom row represent the loss payoff of a bet; (5) each 1 filled blue or red square = 1 PLN; (6) each bet is different from one another at least in one aspect of probability, gain, and loss; and (7) each column represents an alternative bet. Since the bet in Figure 1 contains 75 filled green squares, 17 filled blue squares, and 6 filled red squares , it means that if you play the bet, then you will have a 75% probability of winning 17 PLN and a 25% probability of losing 6 PLN.

Each decision you shall make will involve three bets which are presented on one page. Suppose you have the opportunity to play one among each of three bets. **Please, choose *only one* bet that you would prefer to play among each of three bets** by ticking the appropriate box below this chosen bet. **Please, also try to remember the one that you will choose and the rest two that you will reject in each decision problem,** because we will ask you to recollect your decisions in Task 3. Since each bet is composted of the aforementioned three dimensions (i.e., probability, gain, and loss), remembering a bet that you will choose or reject means that you will have to remember the densities of green, blue, and red squares of the bet. **In order to help you in appropriating remembrance for bets and decisions, we add a unique word for each bet, as shown in the upper left squares of the bottom row (e.g., the word "loteria" in Figure 1).** Therefore, you can also alternatively try to remember these mutually exclusive words, which represent alternative bets, as well as to remember your decisions corresponding to these words. Nevertheless, it is important to note that **your preference for choosing or rejecting a bet should be only based on the probabilities and the gain and loss payoffs of the bet *per se* and should not be based on its attached word**, because

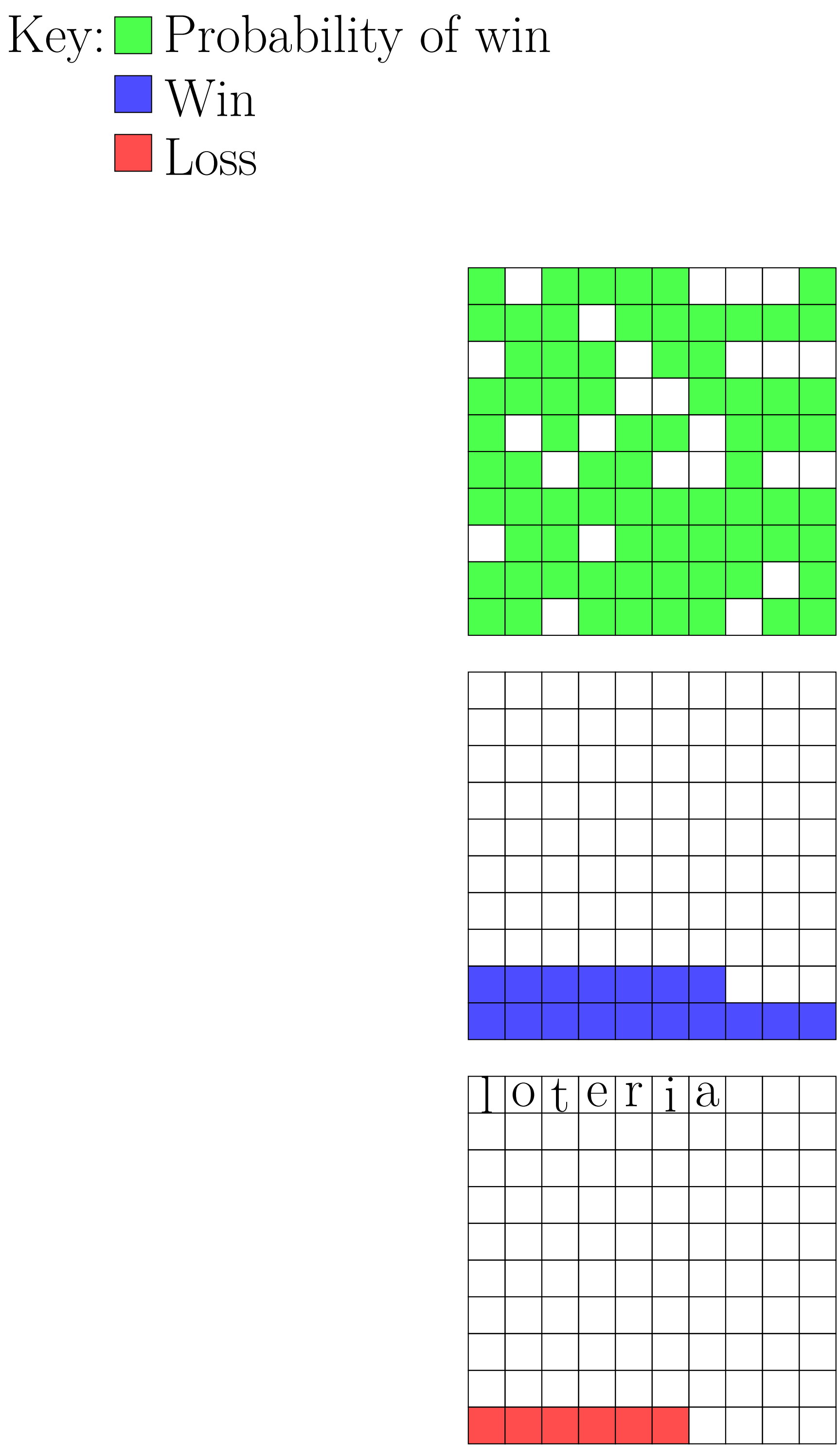


Figure 1: A bet example

the word is intended as just a label of the bet for the purpose of helping you to remember the bet. Please also note that **there is no single "right" choice in any one of these decision problems — different people may have different preferences, and we**

simply want you to tell us *your* personal preference.

Task 2

In this task, suppose that you have been presented, for each of the bets, a ticket that allows you to play a bet. **You will be asked for the *smallest* price at which you would sell the ticket to each of the bets.** Enter this amount in the blank box below the bet (all payoffs are in the Polish Złoty). Again, as for the same reason, **your valuations should be only based on the probabilities and the gain and loss payoffs of the bet *per se* and should not be based on its attached word.**

Task 3

In this task, you will be asked, as mentioned earlier, to recall your choices and rejections made in Task 1. You will be asked to answer "Yes" or "No" to one of the following three types of questions: (1) Did you choose the option?; (2) Did you reject the option?; and (3) Did you choose or reject the option?. Note that some bets would be *new* and would be not presented in Task 1, so answer "No" to them.

PLEASE NOTE: We only care about your recognition memory for your previous choices — please do not assess to your previous choices when you answer the questions in this task.

Earnings

The university foundation has provided funds for conducting this research. At this time, you have received the base 25 PLN remuneration as we expect that **you can complete all the experimental tasks and send back this form to us**. Upon receiving your fully completed forms, we will reimburse you another 25 zł. Moreover, **your additional**

earnings could be up to 25 PLN and depend only partly on your decisions and partly on chance. They will not depend on the decisions of the other participants in the experiment. Please, pay careful attention to the following instructions regarding how your additional earnings are determined, as a considerable amount of money is at stake. We have drawn a random number, *22*, which represents one of those bets, such that you will play out this bet for real. Please note that the probabilities and the gain and loss payoffs of this randomly chosen bet will be unknown to you until we further inform you via email. The rules of bidding for this randomly chosen bet are as follows:

- Another random number between zero and the largest possible outcome of the bet, that is, the amount of gain payoff represented by the density of blue squares (e.g., 17 PLN), will be obtained as an "offer price". Again, we will further inform you this random number via email.

- If the amount of minimum selling price of the bet that you will state in Task 2, say, x PLN, is less than this offer price, you will get additional earnings equal to x PLN. For example, suppose you would be willing to sell the bet in Figure 1 for 10 PLN, that is, x = 10 PLN, which is less than the offer price drawn at random (e.g., 12 PLN), then you would be additionally paid 10 PLN.

- If the x PLN is equal to or greater than this offer price, you will not get any additional earnings. In other words, if the minimum price you state is too high, then you are passing up opportunities that you will gain additional earnings. For example, suppose you would be willing to sell the bet in Figure 1 for 16 PLN, which is instead greater than the random offer price (e.g., 12 PLN), then you would not be additionally paid. Thus, **it is in your own best interests to state minimum amounts at which**

you would indeed sell the bets.

- Because of both the limited amount of the funds designated for the current research and the only face value of 25 PLN of the online Empík e-card, please note that *in practice* if the x PLN is less than the offer price, no matter what the amount of the offer price is, you will be paid **25 PLN**. However, ***IT IS VERY IMPORTANT TO NOTE*** **that a x PLN that you will state for any bet should be based upon the former three rules rather than this practical rule.**

PLEASE NOTE: Your additional earnings will entirely not depend on your performance of memory recollection in Task 3.

Demographic questionnaire

Please provide the following information in the space provided:

1. Age:
2. Gender: Male Female

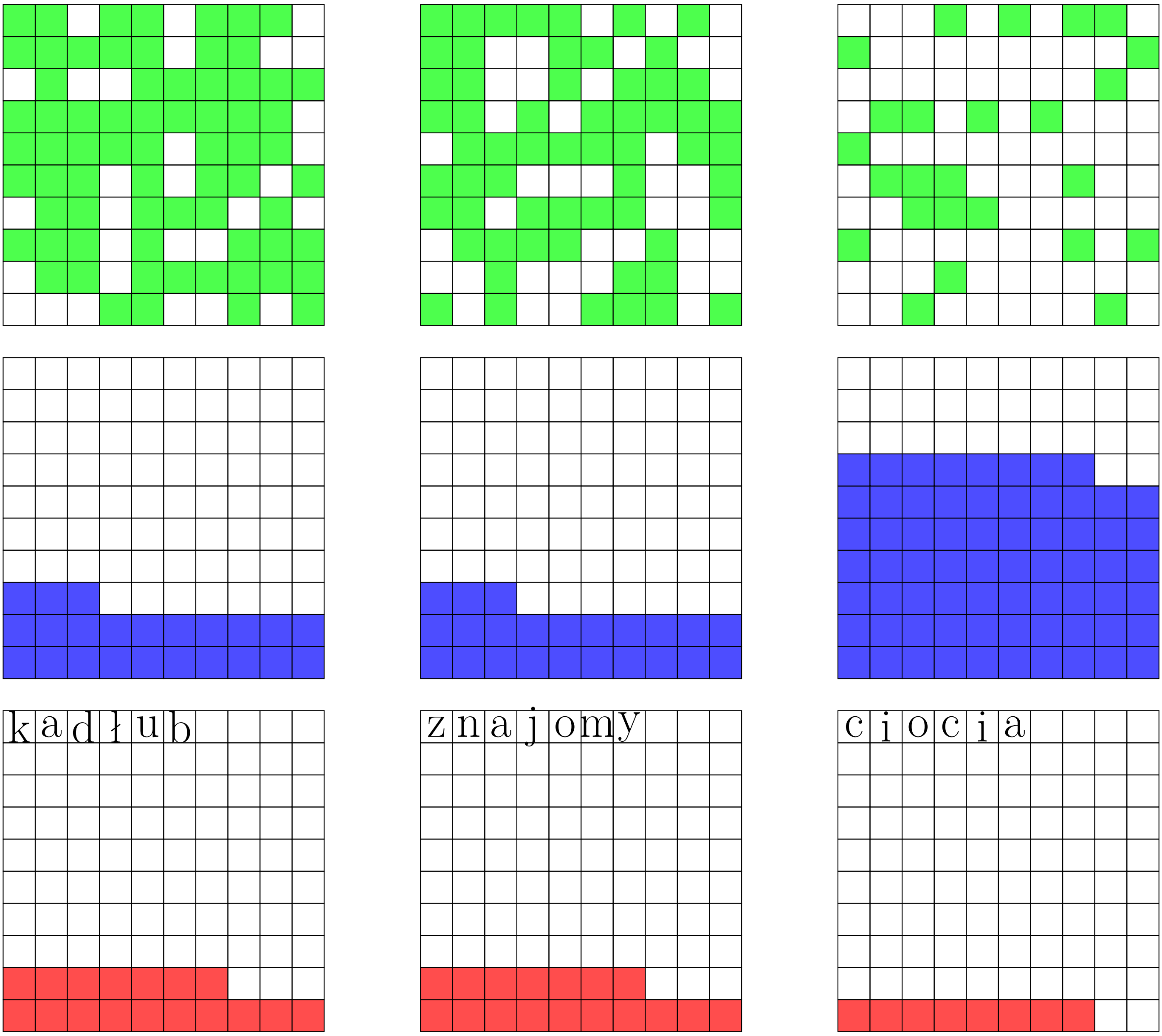
3. If you are a student, please fill out the following information:

- University: UKSW ☐ Other ☐ ;
- Field of study: ☐
- Year: 1st ☐ 2nd ☐ 3rd ☐ 4th ☐

4. Email address: ☐

Task 1 (example)

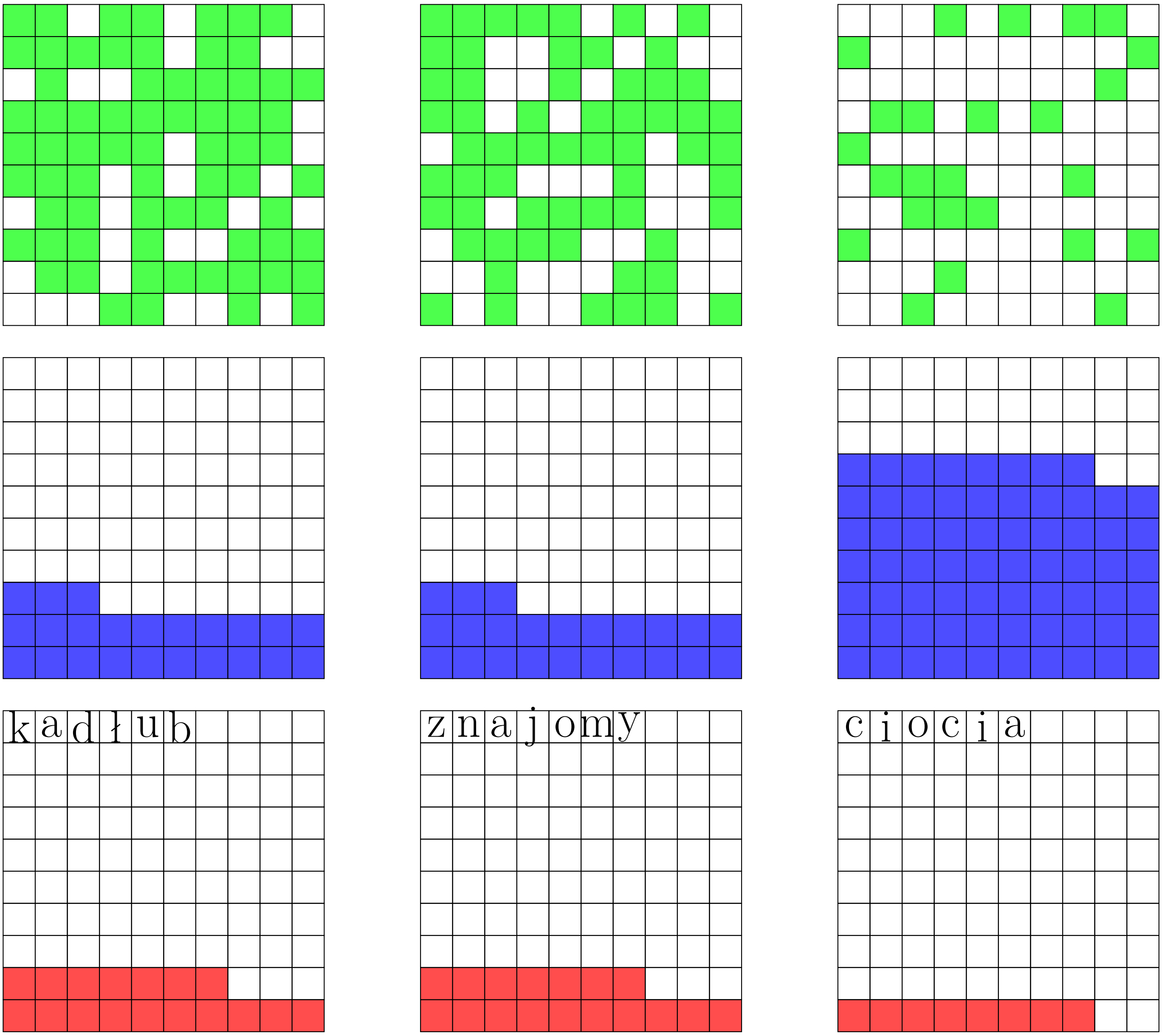
Key: Probability of win
Amount of win
Amount of loss



Choose: Choose: Choose:

Task 2 (example)

Key: Probability of win
Amount of win
Amount of loss

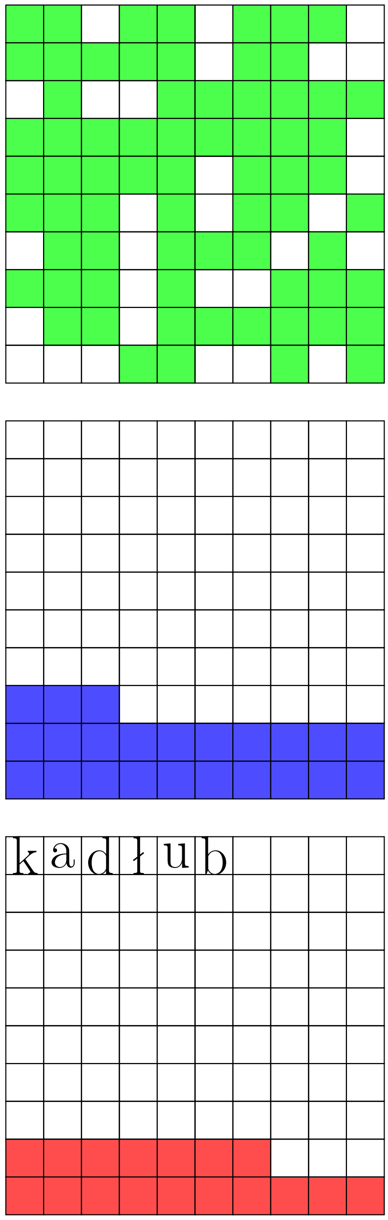


Price:

Price:

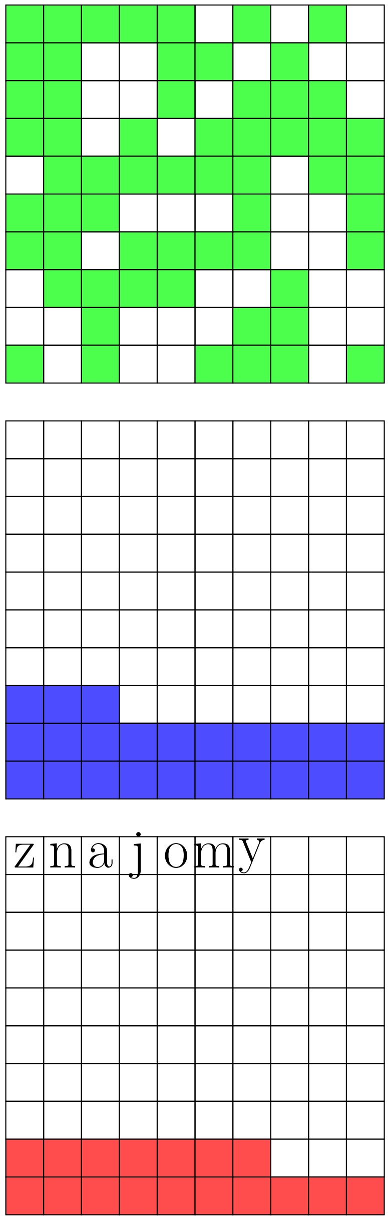
Price:

Task 3 (example)



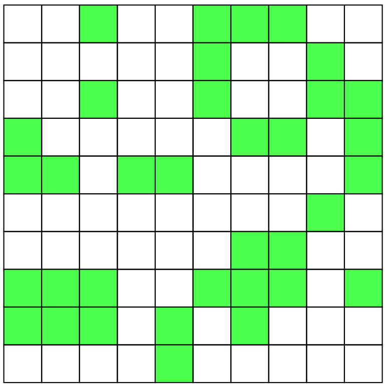
Did you choose the bet?

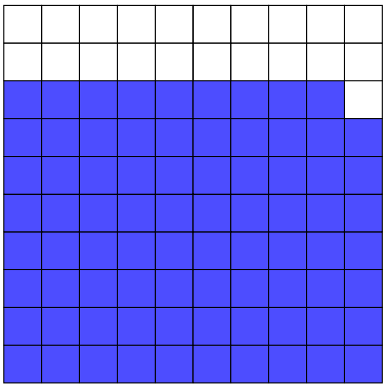
Yes: ☐ No: ☐

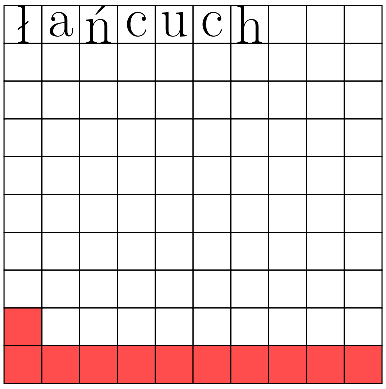


Did you reject the bet?

Yes: $\square$ No: $\square$







Did you choose or reject the bet?

Yes: ☐ No: ☐

Appendix F. Loss aversion parameter ($\boldsymbol{\lambda}$)

Following Tom et al. (2007) and Walasek and Stewart (2015), we estimated the loss aversion parameter (λ) for each individual by fitting a logistic regression to each participant's choice preferences. With the assumption of linear functions for losses and gains differing only in slope, and the neglect of probabilities according to Section 2.2 Heuristic-based binary choice: Explanations by the loss-averse rule, the majority rule, and the equate-to-differentiate rule—thus presumably, equal probability weighting for 0.5, the logistic regression is the same as the prospect theory model with a logistic choice rule:

$$Log[\frac{P(accept)}{1-P(accept)}] = \beta_{bias} + \beta_{gains}gain + \beta_{losses}loss, \tag{F.1}$$

in which the loss aversion λ is the ratio of β_{losses} and β_{gains}, and β_{bias} is an intercept capturing the general tendency of the acceptance preference independent to the loss and gain payoffs. However, the assumption of equal exponents of probability weightings for gains and losses in Equation (F.1) is somehow restrictive due to a need to reduce the number of free parameters, although the assumption turns out to be necessary to permit closed form solutions for analyzing choice decisions in PR. Nevertheless, empirical evidence for this assumption comes from Tversky and Kahneman (1992), who show that participants estimate gain and loss exponents identically as equal to 0.88.

Table F.24 reports median loss aversion coefficients by loss and gain range and by loss ratio. Consistent with the prediction of the decision by sampling model (Walasek and Stewart, 2015), we find loss aversion, with the parameter value being larger than 1, when the range of losses is smaller than that of gains. However, inconsistent with the prediction of the model, we observe that when the ranges are reversed, with the range of losses being larger than that of gains, the parameter value does not drop below 1, signifying prevailing loss aversion indifferent to relative range magnitudes of loss and gain payoffs. The prevailing loss averse preference is most probably because either the low-loss-and-high-gain or high-loss-and-low-gain range is composed of both the low and high loss ratios, as defined in the ranges of -3.0 $\geqslant$ ratios $>$ 0 and ratios $>$ -3.0 at the level of the data in Experiment 2: Binary choices in PR, respectively, and the high loss ratios provoking loss aversion have more impact than the low loss ratios provoking loss loving in each range. The median loss aversion coefficients partitioned by loss ratio partially support this inference in that the sensitivity to loss ratios as a function of the parameter values shows more disparities between loss aversion and its opposite pattern.

Table F.24: Median loss aversion parameter (λ).[a]

	By range		By loss ratio							
	Low loss	High loss								
Data set	High gain	Low gain	-1.0	-1.2	-2.0	-4.0	-6.0	-8.0	-10.0	-23.0
Experiment 2: Binary choices in PR	3.75	4.00	1.15	0.62	5.42	5.41	16.60	1.38	7.17	0.83

[a] Clustered by subject.

Appendix G. Percentages of choice, price valuation, and predicted and unpredicted PR in Experiment 4: Episodic memory in attraction effect PR

The proportionate rates of predicted and unpredicted PR are reported in these entries corresponding to "P-bet" and "$-bet > P-bet" and to "$-bet" and "P-bet > $-bet", respectively. The results of the binomial tests are shown in the "p-value" and "g" entries (see Table G.25).

Table G.25: Percentages of choice, price valuation, and predicted and unpredicted PR: Exact two-sided binomial tests.[a]

	Choice (%)		
Price	P-bet	$-bet	Total
Lotteries 1, 3, 5, and 7 (0%; decoy type = P-bet):			
P-bet > $-bet	10.09	13.25	23.34***
$-bet > P-bet	14.19	56.47	70.66***
P-bet = $-bet	2.21	3.79	6.00
Total	26.49***	73.51***	
p-value	< .001	< .001	.830
g	0.24	0.25	0.02
Lotteries 13 and 15 (50%(↑); decoy type = P-bet):			
P-bet > $-bet	25.97	11.69	37.66
$-bet > P-bet	14.93	38.31	53.24
P-bet = $-bet	4.55	4.55	9.10
Total	45.45	54.55	
p-value	.295	.052	.533
g	0.05	0.09	0.06
Lotteries 21 and 23 (100%(↑); decoy type = P-bet):			
P-bet > $-bet	22.67	19.33	42.00
$-bet > P-bet	12.00	33.33	45.33
P-bet = $-bet	2.67	10.00	12.67
Total	37.34**	62.66**	
p-value	.002	.727	.144
g	0.13	0.02	0.12

	Choice (%)		
Price	P-bet	$-bet	Total
Lotteries 2, 4, 6, and 8 (0%; decoy type = $-bet):			
P-bet > $-bet	8.53	23.93***	32.46***
$-bet > P-bet	9.18***	51.48	60.66***
P-bet = $-bet	1.31	5.57	6.88
Total	19.02***	80.98***	
p-value	< .001	< .001	< .001
g	0.31	0.15	0.22
Lotteries 14 and 16 (50%(↑); decoy type = $-bet):			
P-bet > $-bet	18.13	20.63	38.76
$-bet > P-bet	12.50	39.37	51.87
P-bet = $-bet	3.12	6.25	9.37
Total	33.75***	66.25***	
p-value	< .001	.096	.098
g	0.16	0.07	0.12
Lotteries 22 and 24 (100%(↑); decoy type = $-bet):			
P-bet > $-bet	7.80	24.11*	31.91***
$-bet > P-bet	12.06*	50.35	62.41***
P-bet = $-bet	1.42	4.26	5.68
Total	21.28***	78.72***	
p-value	< .001	< .001	.024
g	0.29	0.16	0.17

	Choice (%)		
Price	P-bet	$-bet	Total
Lotteries 9 and 11 (50%(↓); decoy type = P-bet):			
P-bet > $-bet	11.59	12.19	23.78***
$-bet > P-bet	14.02	58.54	72.56***
P-bet = $-bet	1.83	1.83	3.66
Total	27.44***	72.56***	
p-value	< .001	< .001	.761
g	0.23	0.25	0.04
Lotteries 17 and 19 (100%(↓); decoy type = P-bet):			
P-bet > $-bet	6.02	6.63**	12.65***
$-bet > P-bet	19.28**	60.24	79.52***
P-bet = $-bet	3.61	4.22	7.83
Total	28.91***	71.09***	
p-value	< .001	< .001	.002
g	0.21	0.36	0.24
Lotteries 1 - 24			
P-bet > $-bet	11.67	17.70***	29.37***
$-bet > P-bet	12.24***	51.70	63.94***
P-bet = $-bet	2.20	4.49	6.69
Total	26.11***	73.89***	
p-value	< .001	< .001	< .001
g	0.24	0.19	0.09

	Choice (%)		
Price	P-bet	$-bet	Total
Lotteries 10 and 12 (50%(↓); decoy type = $-bet):			
P-bet > $-bet	9.09	17.53	26.62***
$-bet > P-bet	11.69	57.79	69.48***
P-bet = $-bet	1.95	1.95	3.90
Total	22.73***	77.27***	
p-value	< .001	< .001	.233
g	0.27	0.23	0.10
Lotteries 18 and 20 (100%(↓); decoy type = $-bet):			
P-bet > $-bet	3.95	21.71***	25.66***
$-bet > P-bet	5.92***	65.13	71.05***
P-bet = $-bet	1.32	1.97	3.29
Total	11.19***	88.81***	
p-value	< .001	< .001	< .001
g	0.39	0.24	0.29

[a] (1) The three binomial p-values in each panel show, from left to right, the test statistics of the choice, price valuation, and predicted versus unpredicted PR rates, respectively. (2) The percentages and the significance of the binomial tests are contingent on the exclusion of the responses of those participants who chose decoy bets within the choice task.

* $p < .05$; ** $p < .01$; *** $p < .001$.

Appendix H. Mean correct recollection rates per EVDs and EVLs in Experiment 4: Episodic memory in attraction effect PR

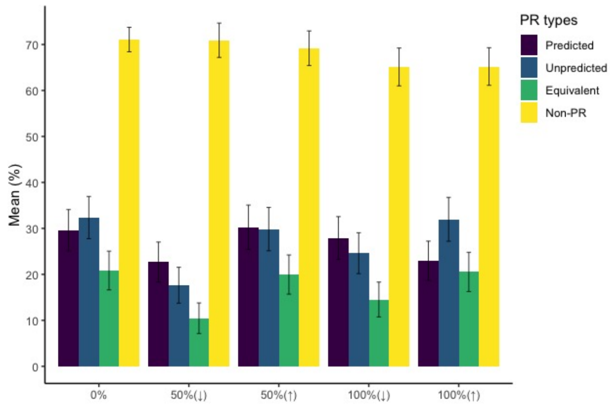
The first category of Table H.26 shows the descriptive findings of the mean correct recollection rates per EVDs (cf., Figure H.24a). A 5 (EVD: 0% vs. 50%(↓) vs. 50%(↑) vs. 100%(↓) vs. 100%(↑)) × 4 (PR type: predicted vs. unpredicted vs. equivalent vs. non-PR) repeated-measures ANOVA on the mean correct recollection rates was conducted. There was a marginally significant main effect of EVD, $F(4,\ 340) = 3.12$, $p = .015$, partial $\eta^2 = 0.01$. As predicted, there was a significant main effect of PR type, $F(3,\ 255) = 73.52$, $p < .001$, partial $\eta^2 = 0.21$. The EVD × PR Type interaction effect was not significant, $F(12,\ 1020) = 0.93$, $p = .516$, partial $\eta^2 = 0.01$.

The second category of Table H.26 shows the descriptive findings of the mean correct recollection rates per EVLs (cf., Figure H.24b). A 2 (EVL (median split): low vs. high) × 4 (PR type: predicted vs. unpredicted vs. equivalent vs. non-PR) repeated-measures ANOVA on the mean correct recollection rates was conducted. As predicted, there was a significant main effect of PR type, $F(3,\ 255) = 25.08$, $p < .001$, partial $\eta^2 = 0.13$. The main effect of EVL was not significant, $F(1,\ 85) = 0.60$, $p = .442$, partial $\eta^2 = 0.00$. The EVL × PR Type interaction effect was not significant, $F(3,\ 255) = 0.87$, $p = .436$, partial $\eta^2 = 0.00$.

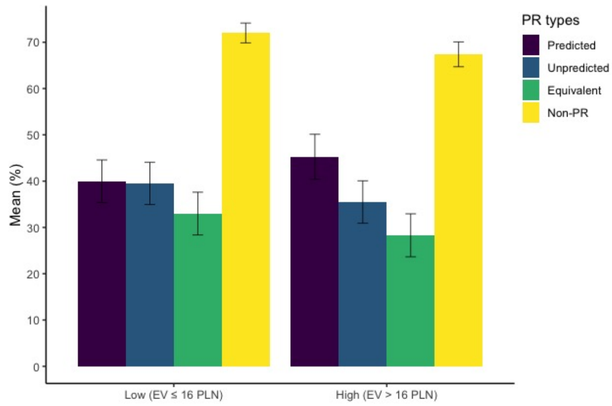
Table H.26: Mean correct recollection rates (%) per EVDs, EVLs, and PR types.[a]

No.	Categories	Subcategories	PR types: Predicted	Unpredicted	Equivalent	Non-PR
1	EVDs	0%	29.59 (41.66)	32.36 (42.57)	20.83 (39.14)	71.09 (24.65)
		50%(↓)	22.67 (40.34)	17.64 (36.10)	10.47 (30.79)	70.93 (34.63)
		50%(↑)	30.23 (44.91)	29.85 (43.77)	19.96 (39.51)	69.19 (35.01)
		100%(↓)	27.91 (43.12)	24.61 (41.28)	14.53 (35.04)	65.12 (38.04)
		100%(↑)	22.97 (39.52)	31.98 (44.28)	20.54 (39.58)	65.21 (37.99)
2	EVLs (median split)	Low (EV $\leqslant$ 16 PLN)	39.98 (42.60)	39.51 (42.45)	32.98 (42.90)	72.01 (19.79)
		High (EV $>$ 16 PLN)	45.26 (45.04)	35.49 (42.56)	28.30 (43.09)	67.40 (24.95)

[a] Standard deviations are reported in parentheses.



(a) EVDs



(b) EVLs

Figure H.24: Mean correct recollection rates per (a) EVDs and (b) EVLs.
Note: Error bars are the ±1 standard error of the mean.

Appendix I. The "play-out" and "payment" effects

When the different preference induced by the two choice and price PR tasks is large, reversals are the result of systematic deviations from stable preferences. However, reversals could also be the result of random (non-systematic) errors, something which are termed as "noisy maximization" (Berg, Dickhaut and Rietz, 2003). The model of noisy maximization would accommodate data patterns where preferences are elicited using played-out gambles with either truth-revealing monetary or even unpaid payments rather than purely hypothetical gambles. Berg et al. (2013) documented the so-called "play-out" and "payment" (incentives) effects. Previous research indicates that compared with elicitation-based PR in terms of purely hypothetical gambles as stimuli, providing a certain sort of monetary rewards or incentives to participants generates truly stable risk preferences (Berg et al., 2010, 2013; Miller, Hofstetter, Krohmer and Zhang, 2011) and rational choice responses to high-payoff alternatives (Shanks, Tunney and McCarthy, 2002).

This "play-out" effect is argued to accord with traditional Lichtenstein and Slovic's (1971) two-error-rate model and Smith's (1976) incentive-induced value model in context. All these three models assume a "payment" effect that individuals are able to declare more coherent preferences across tasks by means of the proper use of a reward medium. This is presumably because incentive payments based on the outcomes of subjects' decisions can create a clearly defined objective function (cf., Camerer and Hogarth, 1999; Hsee, Yu, Zhang and Zhang, 2003) or increase risk sensitivity (Selten et al., 1999). In what follows, we first outline an issue regarding the two-error-rate model and propose an adapted model of it. Then, we examined the two effects by this model across our three experiments, in which we elicited preferences by manipulating three independent treatments, either using purely hypothetical bets or played-out bets without or with paying subjects based on payoffs.

Appendix I.1. The noisy maximization (three-error-rate) model

The two-error-rate model (Lichtenstein and Slovic, 1971) assumes that (1) individuals have stable preferences across bets but (2) reveal oppositely due to the unreliability of random responses, where tasks neither affect preferences, nor do preferences affect error rates. However, the model does not provide insights substantiating how the behavior of tied valuations on pairs of lotteries is explained, which reflects neither reversal nor consistency; instead, the behavior is either included in the category where either P-bets or $-bets are priced higher or simply excluded. (For a somewhat different model, labeled as expression theory, leading to the same statistical test for the presence of PR, see Goldstein and Einhorn, 1987.) First, any inclusion of the behavior is not in accordance with standard theory, since the strict preference, say, choosing the P-bet over the $-bet, is incongruous with the deviating valuation price, that is, evaluating the $-bet higher than the P-bet, and the ties, that is, evaluating the P-bet and the $-bet equally. Second, any exclusion of the behavior results in an incomplete data analysis with regard to risk preferences within choice tasks.

In order to accommodate the behavior of tied valuations, we propose to extend the model to a three-error-rate one. To parameterize the new model, as constructed similarly as the two-error-rate model, (1) let p represents the percentage of subjects who truly prefers the P-bet within both the choice and price tasks; (2) let x represents the error rate at which the non-preferred bet is chosen within the choice task; (3) let y represents the error rate at which the non-preferred bet is evaluated higher; and (4) let z represents the error rate at which the preferred and non-preferred bets are evaluated equivalently—a parameter which is not substantiated in the two-error-rate model. The probabilities of all possible observations generated in a classic PR experiment are shown in Table I.27, where a, b, c, d, e, and f represent these probabilities that fall into each cell. Following the assumption of the two-error-rate model that the error rates are independent across tasks, these cell proportions are independent and thus yield the following three equations in the four unknowns, p, x, y, and z. Notice that (1) the equation (I.1) may not have a real solution for p; (2) the estimate of $\hat{p}$ = 50% may fail to determine the estimates of $\hat{x}$ and $\hat{y}$ + $\hat{z}$ according to the equations (I.2) and (I.3), respectively; and (3) other estimates of $\hat{p}$, $\hat{x}$, and $\hat{y}$ + $\hat{z}$ may also fall outside the valid 0-100% probability range.

$$\hat{p}(1-\hat{p}) = \frac{ad-bc}{(a+d+f)-(b+c+e)}, \tag{I.1}$$

$$\hat{x} = \frac{a+c+e-\hat{p}}{1-2\hat{p}}, \tag{I.2}$$

and

$$\hat{y}+\hat{z} = \frac{a+b-\hat{p}}{1-2\hat{p}}. \tag{I.3}$$

Appendix I.2. Hypothetical, played-out, and incentive inductions

The adapted three-error-rate model allows us to examine precisely whether our data are consistent with noisy maximization. Table I.28 presents summary data across treatments (cf., Figure I.25). The first row (labeled NP-NI) is the treatment in which lotteries were not played-out, and subjects were not paid. The second row (labeled P-NI) is the treatment in which lotteries were played-out, but subjects were not paid. The third row (labeled P-I) is the treatment in which lotteries were played-out, and subjects were paid. A P-bet preference or

Table I.27: Three-error-rate model: An extension of the Lichtenstein and Slovic's (1971) two-error-rate model.[a]

	Choice (%)		
Price	P-bet	\$-bet	Total
P-bet > \$-bet	p(1-x)(1-y-z) + (1-p)x(y+z) *a*	px(1-y-z) + (1-p)(1-x)(y+z) *b*	p(1-y-z) + (1-p)(y+z)
\$-bet > P-bet	p(1-x)y + (1-p)x(1-y) *c*	pxy + (1-p)(1-x)(1-y) *d*	py + (1-p)(1-y)
P-bet = \$-bet	p(1-x)z + (1-p)x(-z) *e*	pxz + (1-p)(1-x)(-z) *f*	pz + (1-p)(-z)
Total	p(1-x) + (1-p)x	px + (1-p)(1-x)	1

[a] p: Percentage of subjects whose underlying risk preference ranks the P-bet higher; x: Error rate within the choice task; y: Error rate within the price task, where the non-preferred bet is evaluated higher; z: Error rate within the price task, where the preferred and non-preferred bets are evaluated equivalently.

PR rate is calculated as an aggregate frequency in a specified data range divided by the total observation. For example, we compute a preference rate for P-bets within the choice task as

$\frac{\sum_{j=1}^{n} a + \sum_{j=1}^{n} c + \sum_{j=1}^{n} e}{\sum_{j=1}^{n} a + \sum_{j=1}^{n} b + \sum_{j=1}^{n} c + \sum_{j=1}^{n} d + \sum_{j=1}^{n} e + \sum_{j=1}^{n} f}$, where n refers to the total number of the lotteries in the specified data range. As the summary statistics of the aggregate data, no statistical modeling can not be applied to test hypotheses, Thus, the following analyses are exploratory.

The results reveal that (1) played-out bets weaken incongruent risk preferences, even without payoff-contingent incentives tied to bets; (2) a combination of the effects leads to even more congruent risk preferences across the choice and price tasks; and (3) PR rates themselves are largely unaffected by the "play-out" or payment treatment. Our data confirm Berg et al.'s (2013) findings in that compared with preferences elicited by using purely hypothetical bets (Experiment 1: Magnitude effects in PR), those induced by using played-out bets, either in the absence of payments (Experiment 3: Episodic memory in PR) or with paying subjects based on payoffs (Experiment 4: Episodic memory in attraction effect PR), shift the overall response pattern by inducing a more stable underlying preference function over gambles.

While there is a reduction effect on the total level of difference between preference measures across the choice and price tasks (the differences drop from 31.59% to 22.16% to 0.26%), there is no obvious effect on the percentage of times that P-bets are preferred when lotteries have *low* loss or gain ratios (the differences are 15.25% and 15.99%). Instead, large differences in preferences between the choice and price tasks occur when lotteries have *high* loss or gain ratios (the differences drop from 47.65% to 31.08%). It should be noted, however, that it is uncertain to what extent the two effects arose as a determinant and consequence to attenuate the disparity of risk preferences between choices and valuations of bets, since the three experiments also considerably differed in other various aspects of decision context

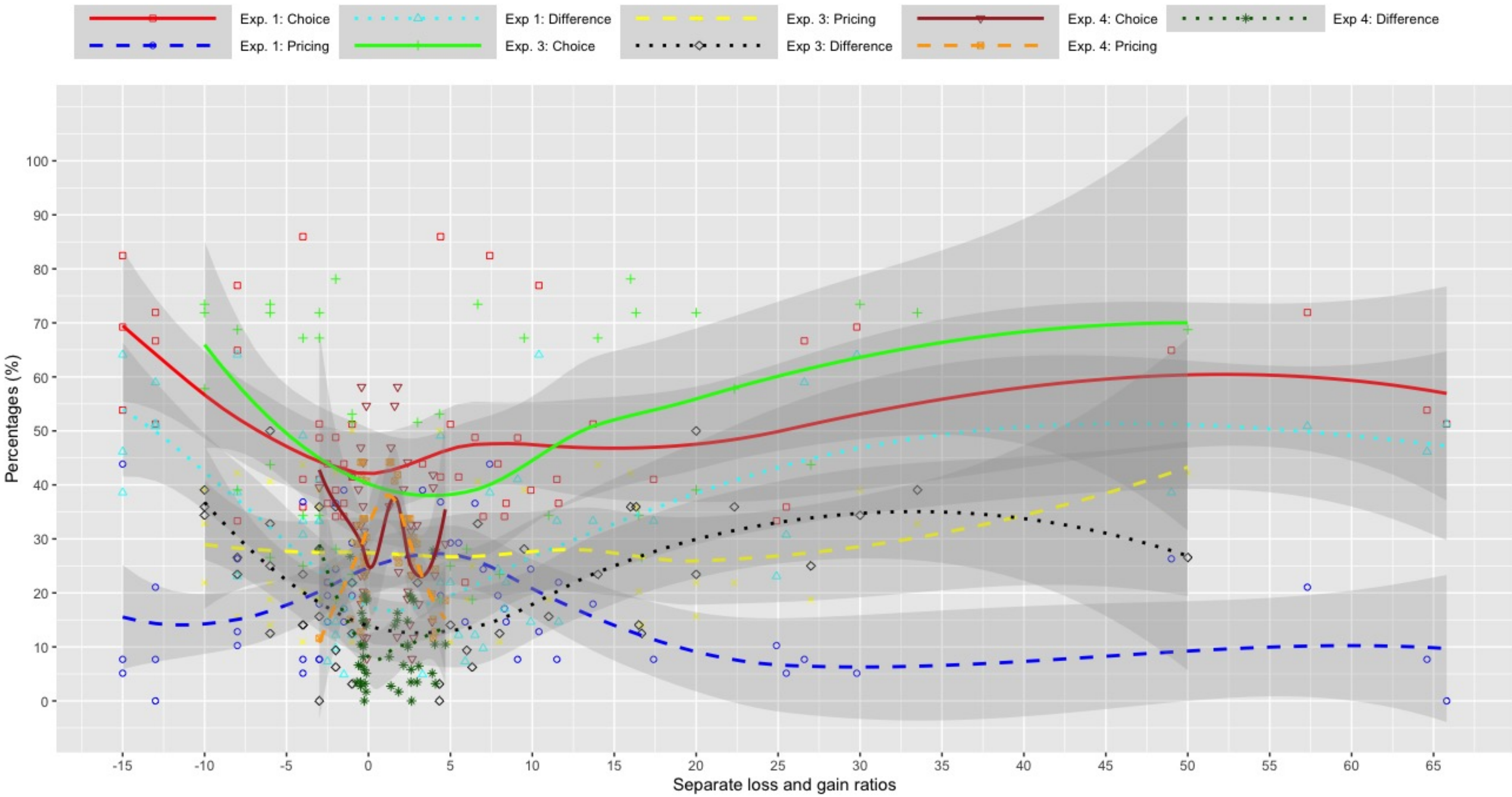


Figure I.25: P-bet preferences across treatments in Experiment 1: Magnitude effects in PR, Experiment 3: Episodic memory in PR, and Experiment 4: Episodic memory in attraction effect PR: Low versus high loss or gain ratios as determiners.
Note: The regression curves of the P-bet preferences within the choice and price tasks and their differences are graphed in solid, dashed, and dotted lines, respectively. The shaded curves show the nonlinear (LOESS) regression functions with 95% confidence bands.

Table I.28: Aggregate P-bet preferences and PR rates of the three-error-rate model across treatments: Low versus high loss or gain ratios as the determinant.

			Three-error-rate model											
			Aggregate preference for P-bets within choice tasks (%)[b]			Aggregate preference for P-bets within pirce tasks (%)[c]			Difference between P-bet preference measures (%)			Aggregate PR rates (%)[d]		
"Play-out" and incentives treatments[a]	Data set	Total obs.	Low loss/gain ratios	High loss/gain ratios	Total	Low loss/gain ratios	High loss/gain ratios	Total	Low loss/gain ratios	High loss/gain ratios	Total	Low loss/gain ratios	High loss/gain ratios	Total
NP-NI	Experiment 1: Magnitude effects in PR[e]	1149	39.44	64.69	51.35	24.19	17.04	19.76	15.25	47.65	31.59	29.47	42.47	36.29
P-NI	Experiment 3: Episodic memory in PR[f]	1408	43.99	58.51	49.93	28.00	27.43	27.77	15.99	31.08	22.16	37.38	43.58	39.92
P-I	Experiment 4: Episodic memory in attraction effect PR	1944	29.73	N/A[g]	29.73	29.99	N/A[g]	29.99	0.26	N/A[g]	0.26	30.43 (42.59)	N/A[g]	30.43 (42.59)

[a] NP or P indicate whether bets were Not Played-out or Played-out; NI or I indicate that No (monetary) Incentives were tied to bet payoffs or (monetary) Incentives were tied to bet payoffs (cf., Berg et al., 2013).

[b] I.e., $\dfrac{a+c+e}{a+b+c+d+e+f}$. See Table I.27 for the definations of the quantities a, b, c, and d.

[c] I.e., $\dfrac{b+d+f}{a+b+c+d+e+f}$.

[d] I.e., $\dfrac{b+c}{a+b+c+d+e+f}$. The PR rate in parentheses in Experiment 4: Episodic memory in attraction effect PR is measured as the mean of absolute values of proportional differences between target and competitor choices, that is, the contextual choice PR rate (Farmer et al., 2017).

[e] (1) -1.0 $\leqslant$ low loss ratio $\leqslant$ -2.5; (2) 5.0 $\leqslant$ low gain ratio $\leqslant$ 8.5; (3) -8.0 $\leqslant$ high loss ratio $\leqslant$ -15.0; and (4) 28.1 $\leqslant$ high gain ratio $\leqslant$ 49.9.

[f] (1) -1.0 $\leqslant$ low loss ratio $\leqslant$ -4.0; (2) 5.1 $\leqslant$ low gain ratio $\leqslant$ 13.6; (3) -6.0 $\leqslant$ high loss ratio $\leqslant$ -10.0; and (4) 17.9 $\leqslant$ high gain ratio $\leqslant$ 35.0.

[g] N/A = not applicable.

(see Spektor, Bhatia and Gluth, 2021 for a recent discussion).

Appendix I.3. Conditional PR

Conditional PR reflects the reversal of preference in one task conditional on the corresponding preference in the other task (Grether and Plott, 1979; Lichtenstein and Slovic, 1971). Table I.29 shows the conditional PR rates (i.e., the reversal rate in the choice or price task conditional on the price valuation or choice, respectively; that is, $\frac{c}{a+c}$ and $\frac{b}{b+d}$ for the P-bet and \$-bet, respectively, within the choice task; and $\frac{b}{a+b}$ and $\frac{c}{c+d}$ for the P-bet and \$-bet, respectively, within the price task; cf., Table I.27), as broken down by the low, high, and overall loss or gain ratios. Specifically, these reversal rates are the average values in the given data ranges, that is, for example, $\frac{\sum_{j=1}^{n} \frac{c_j}{a_j + c_j}}{n}$ for the P-bets within the choice task, where n refers to the total number of the lotteries in a specified data range. We computed the reversal rate for each bet pair (i.e., $\frac{c_j}{a_j + c_j}$) in order to perform quantitative statistical analyses.

Paired t-tests reveal that across all the treatments, first, the mean reversal rates significantly more skyrocketed for the P-bets than the \$-bets within the choice tasks (all $p <$ .001). In other words, the participants who chose the P-bets more reversed (at lease 58.22% of the time) than those who chose the \$-bets (at most 29.00% of the time) within the price tasks. Second, the mean reversal rates also significantly more exceeded for the \$-bets than the P-bets under the condition of the high loss or gain ratios within the price task (all $p <$ .001). In other words, when the lotteries have the high loss or gain ratios, the participants who priced the \$-bets higher more reversed (at least 56.86% of the time) than those who priced the P-bets higher (at most 32.92% of the time) within the choice tasks. Overall, these results across the treatments did not differ strongly. Therefore, it seems that Berg et al.'s

Table I.29: Conditional PR rates across treatments.

"Play-out" and incentives treatments[a]	Data set	Loss/gain Ratio	Obs.	Conditional PR rates (%): The choice task: P-bets $\frac{c}{a+c}$[b]	$-bets $\frac{b}{b+d}$[b]	Differences	The price task: P-bets $\frac{b}{a+b}$[b]	$-bets $\frac{c}{c+d}$[b]	Differences
NP-NI	Experiment 1: Magnitude effects in PR	Low	492	58.22	21.11	37.11	44.52	31.73	12.78
		High	405	73.30	7.88	65.42	14.50	58.06	-43.56
		Total	1149	69.15	15.61	63.54	32.59	46.17	-13.58
P-NI	Experiment 3: Episodic memory in PR	Low	832	62.51	29.00	33.51	49.79	40.72	9.07
		High	576	65.25	25.62	39.63	32.92	56.86	-23.94
		Total	1408	63.85	27.85	36.00	42.96	47.52	-4.56
P-I	Experiment 4: Episodic memory in attraction effect PR	Low	1944	56.35	25.75	30.60	61.10	22.74	38.36
		High	N/A[c]	N/A[c]	N/A[c]	N/A[c]	N/A[c]	N/A[c]	N/A[c]

[a] NP or P indicate whether bets were Not Played-out or Played-out; NI or I indicate that No (monetary) Incentives were tied to bet payoffs or (monetary) Incentives were tied to bet payoffs (cf., Berg et al., 2013).
[b] Values outside and in parentheses are the average and aggregate reversal rates. See Table I.27 for the definations of the quantities a, b, c, and d.
[c] N/A = not applicable.

(2013) noisy maximization models with random errors could not explain the data patterns we observe.

Appendix I.4. Price valuations

We further examine whether the purely hypothetical, "play-out", and payment treatments appear in pricing judgments by means of deviations from EVs and from certainty equivalents by alternative benchmark theories of risky decision making.

Appendix I.4.1. Deviations from EVs

Figure I.26 shows average price valuations for each bet under each treatment. The regression curves of the P-bets and \$-bets in each pair under each treatment are graphed in solid and dotted lines of the same color, respectively. As seen by the visual detection, the \$-bet price valuations exceed the paired P-bet price valuations across all the three treatments. Paired two-sample t-tests further confirm that the mean median price valuations were significantly different between the P-bets and \$-bets (1) in Experiment 1: Magnitude effects in PR, $t(26) = 7.11$, $p < .001$, $d = 1.37$; $M_\Delta = 5.6$ PLN, $SE = 0.8$ PLN; (2) in Experiment 3: Episodic memory in PR, $t(10) = 5.01$, $p < .001$, $d = 1.51$; $M_\Delta = 29.1$ PLN, $SE = 5.8$ PLN; and (3) in Experiment 4: Episodic memory in attraction effect PR, $t(23)_{\text{targets}} = 4.02$, $p < .001$, $d = 0.82$; $M_\Delta = 4.0$ PLN, $SE = 1.0$ PLN; $t(11)_{\text{decoys}} = 2.88$, $p = .0015$, $d = 0.83$; $M_\Delta = 4.9$ PLN, $SE = 1.7$ PLN.

More specifically, Experiment 1: Magnitude effects in PR shows some divergence of price valuation between bet pairs. The price valuations are, on average, lower than EVs, as shown by the data points that are below the identity line, which indicates that subjects are generally risk averse (see The price task for a discussion). Paired two-sample t-tests further confirm that the P-bets and \$-bets were significantly different between their mean median price

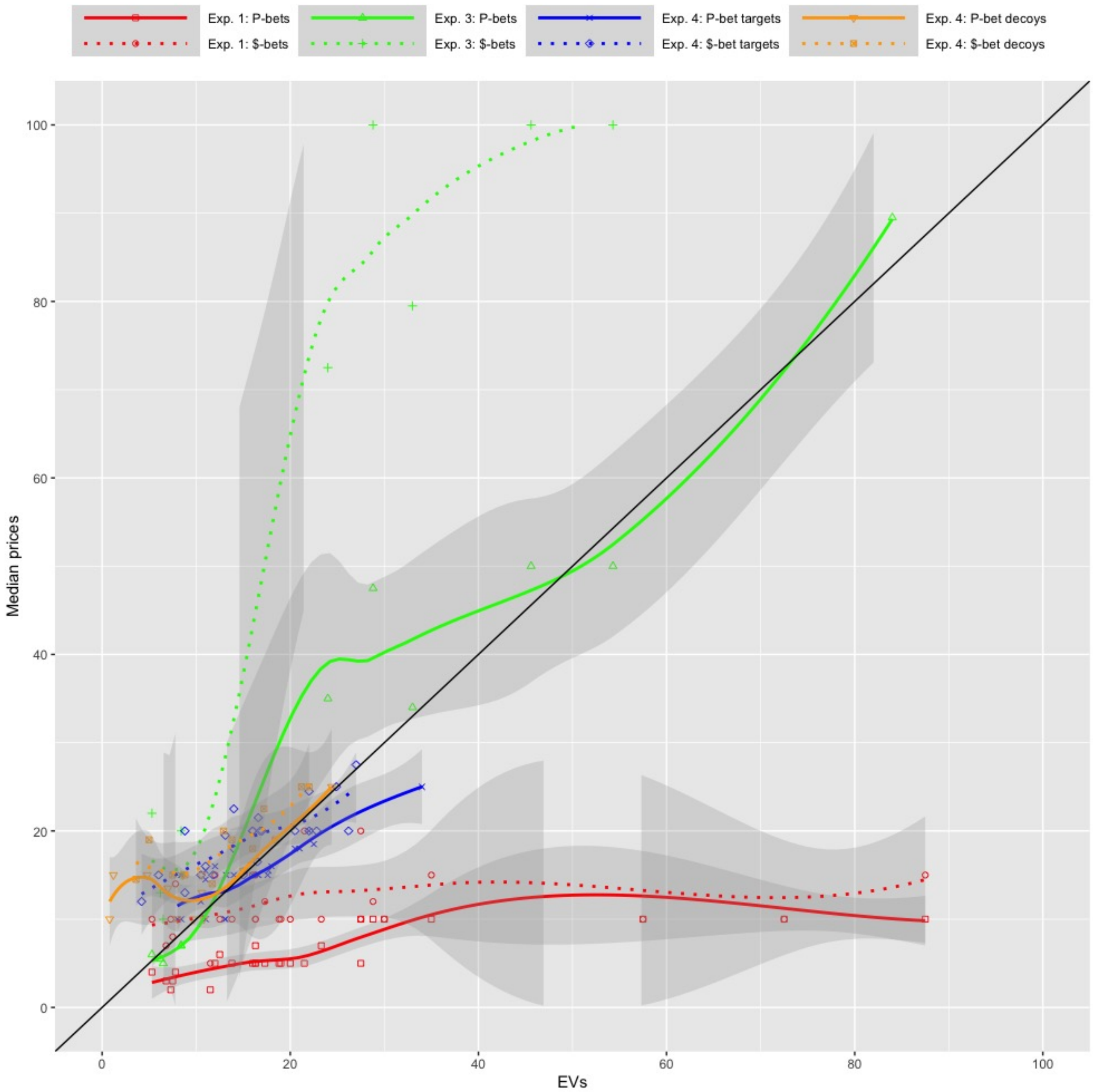


Figure I.26: Median price valuations of bets by treatment.
Note: A total of 11 bet pairs whose EVs exceed 100 PLN in Experiment 3: Episodic memory in PR are excluded from the analysis. The shaded curves show the nonlinear (LOESS) regression functions with 95% confidence bands.

valuations and EVs, respectively, $t(26)_{\text{P-bets}} = 5.13$, $p < .001$, $d = 0.99$; $M_{\Delta} = 17.5$ PLN, $SE = 3.4$ PLN; $t(26)_{\text{\$-bets}} = 3.22$, $p = .003$, $d = 0.62$; $M_{\Delta} = 12.0$ PLN, $SE = 3.7$ PLN.

Experiment 3: Episodic memory in PR shows increasing divergence. The price valuations are, on average, higher than EVs, as shown by the data points that are above the identity line, which indicates that subjects are general risk seeking. Paired two-sample t-tests indicate that

(1) the P-bets were not significantly different between their mean median price valuations and EVs, $t(10) = 1.43$, $p = .183$, $d = 0.43$; $M_{\Delta} = 2.91$ PLN, $SE = 2.0$ PLN; but (2) they were significantly different for the \$-bets, $t(10) = 4.52$, $p = .001$, $d = 1.36$; $M_{\Delta} = 32.1$ PLN, $SE = 7.1$ PLN.

Experiment 4: Episodic memory in attraction effect PR also shows some divergence. The price valuations and EVs align closely, as shown by the data points that are close to the identity line, which indicates that subjects are approximately risk neutral. Paired two-sample t-tests indicate that (1) the target P-bets were not significantly different between their mean median price valuations and EVs, $t(23) = 0.73$, $p = .475$, $d = 0.15$; $M_{\Delta} = 0.5$ PLN, $SE = 0.7$ PLN; but (2) they were significantly different for the decoy P-bets and target and decoy \$-bets, $t(11)_{\text{decoy P-bets}} = 3.46$, $p = .005$, $d = 1.00$; $M_{\Delta} = 4.6$ PLN, $SE = 1.3$ PLN; $t(23)_{\text{target \$-bets}} = 3.10$, $p < .001$, $d = 0.77$; $M_{\Delta} = 3.1$ PLN, $SE = 0.8$ PLN; $t(11)_{\text{decoy \$-bets}} = 5.08$, $p < .001$, $d = 1.47$; $M_{\Delta} = 5.7$ PLN, $SE = 1.1$ PLN.

Taken together, the induced divergence and the opposite risk preferences between the no incentives and played-out treatments are possibly because of noise or imprecision introduced by the two different risk preference procedures. As seen by comparing the no incentives and played-out but unpaid or incentives treatments, the latter two seem to make subject behavior towards (target) P-bets more conform to expected utility theory. Generally speaking, as expected, the so-called “play-out” and “payment” effects appear stronger for less risky P-bets than riskier \$-bets. Again, it should be noted that it is uncertain to what extent these treatments attributed in the findings due to that the experimental materials, designs, and procedures are all considerably divergent from each other. Any the interpretations are strictly speculative.

Appendix I.4.2. Deviations from certainty equivalents

The certainty equivalent of a bet is the lowest amount of money-for-certain that a decision maker would be willing to accept instead of the bet. That is, saying that $100 is the certainty equivalent of a bet that would pay the decision maker either $300 or $0, each with probability 1/2, means that the decision maker would be just indifferent between having a ticket to this bet or having $100 cash in hand. The theoretical certainty equivalent (abbreviated ce) of a P-bet or $-bet can be computed as follows:

$$\mathrm{ce}_{\text{P-bet}} = \frac{\ln[p_{\mathrm{P}} e^{\gamma v_{\mathrm{P}}^{-}} + (1 - p_{\mathrm{P}}) e^{\gamma v_{\mathrm{P}}^{+}}]}{\gamma}, \tag{I.4}$$

or

$$\mathrm{ce}_{\text{\$-bet}} = \frac{\ln[p_{\$} e^{\gamma v_{\$}^{-}} + (1 - p_{\$}) e^{\gamma v_{\$}^{+}}]}{\gamma}, \tag{I.5}$$

where (1) p_{P} and $p_{\$}$ are the probabilities of winning positive payoffs v_{P}^{+} and $v_{\$}^{+}$ in the P-bet and $-bet, respectively; (2) v_{P}^{-} and $v_{\$}^{-}$ are negative payoffs in the P-bet and $-bet, respectively; and (3) γ is the parameter representing constant risk tolerance that varies its value in different benchmark theories (Luce, 1992). We calculated certainty equivalents using the `pt` package in the statistical programming language R 4.2.1 (Au, 2014).

The alternative theories of risky decision making, including expected utility theory (both concave and convex), prospect theory, (low) gains decomposition utility theory, rank-dependent utility theory, and subjectively weighted average utility theory that will be introduced below, allow us to benchmark our results and place them in context. We can compare those certainty equivalents to actual price valuations to examine which benchmark theories best match our empirical data.

Appendix I.4.2.1 Expected utility theory

von Neumann and Morgenstern (1953) axiomatized expected utility theory as a normative, as well as a descriptive, model of decision making, specifying how people ought to make decisions. The coral assumption of the theory has been that, to an approximation, people make decisions that maximize their utility and that judge a risky prospect, in general, (v_1, p_1; v_2, p_2; ... ; v_n, p_n) with n payoffs, by a probabilistic sense of expectation called expected utility (eu), as expressed by $U(v_1,\ p_1;\ v_2,\ p_2;\ ...\ ;\ v_n,\ p_n)$, where the function U denotes the expected utility of the risky prospect, the payoffs v_i occurs with a probability of p_i ($1 \leqslant i \leqslant n$), and $\sum_{i=1}^{n} p_i = 1$. The theory has played a key role in theories of rational choice since its establishment. Then,

$$\text{eu}(v_1, p_1; v_2, p_2; ...; v_n, p_n) = \sum_{i=1}^{n} p_i u(v_i), \tag{I.6}$$

where the function $u(v_i)$ is reserved for the utility of single payoff v_i only. The eu is represented by a hypothetical concave or convex utility function for modeling risk aversion (Tversky, 1975). Take the P-bet = (p_P, v^+_P; 1 - p_P, v^-_P) for example. According to the theory, (1) eu(P-bet)$_\text{concave}$ = $p_\text{P} u(v^+_\text{P})$ + (1 - p_P)$u(v^-_\text{P})$, where $u(v^+_\text{P}) = {v^+_\text{P}}^{0.63}$ and $u(v^-_\text{P})$ = -2.25(-v^-_P)$^{0.63}$ (cf., Figure I.28a); and (2) eu(P-bet)$_\text{convex}$ = $p_\text{P} u(v^+_\text{P})$ + (1 - p_P)$u(v^-_\text{P})$, where $1 > p_\text{P} > 0$, $v^+_\text{P} > 0 > v^-_\text{P}$, $u(v^+_\text{P}) = {v^+_\text{P}}^{1.2}$, and $u(v^-_\text{P})$ = -2.25(-v^-_P)$^{1.2}$ (cf., Figure I.28b).

Appendix I.4.2.2 Prospect theory

Kahneman and Tversky (1979) introduced prospect theory as a model of risky decision making, and present it as a critique of expected utility theory.

$$u(v) = \begin{cases} v^{\beta}, & \text{if } v \geqslant 0 \\ -\lambda| - v|^{\beta}, & \text{if } v < 0, \end{cases} \tag{I.7}$$

where β represents a parameter characterizing subjects' sensitivity to the potential gain and loss payoffs; and λ is a loss aversion coefficient, describing subjects' fear from losses. Following Kudryavtsev and Pavlodsky (2012), we assume that λ is equal for gains and losses.

$$w(p) = \frac{p^{\alpha}}{[p^{\alpha} + (1-p)^{\alpha}]^{(1/\alpha)}}, \tag{I.8}$$

where α gives a mathematical interpretation to the shape of subjective probability function, as represented by overweighting small probabilities and underweighting high probabilities, and α is equal for gains and losses. The function is only strictly increasing for $\alpha \geqslant 0.28$. Specifically, for two-payoff bets, decision weights $w(p)$ typically exceed small objective probabilities, but are less than most objective probabilities. More precisely, $w(p) > p$ for small p, and $w(p) + w(1 - p) < 1$ for all p. According to the theory, ptu(P-bet) $=$ w$(p_{\mathrm{P}})u(v_{\mathrm{P}}^{+})$ + w$(1 - p_{\mathrm{P}})u(v_{\mathrm{P}}^{-})$, where w$(p_{\mathrm{P}}) = \frac{{p_{\mathrm{P}}}^{0.61}}{[{p_{\mathrm{P}}}^{0.61} + (1-p_{\mathrm{P}})^{0.61}]^{(1/0.61)}}$, w$(1 - p_{\mathrm{P}}) = \frac{(1-p_{\mathrm{P}})^{0.61}}{[(1-p_{\mathrm{P}})^{0.61} + {p_{\mathrm{P}}}^{0.61}]^{(1/0.61)}}$, $u(v_{\mathrm{P}}^{+}) = {v_{\mathrm{P}}^{+}}^{0.88}$, and $u(v_{\mathrm{P}}^{-}) = -2.25(-v_{\mathrm{P}}^{-})^{0.88}$ (cf., Figure I.28c; see also Baláž, Bačová, Drobná, Dudeková and Adamík, 2013).

Appendix I.4.2.3 (Lower) gains decomposition utility theory

Luce (2000, p. 202) derived an induction formula for multi-branch prospects which could be decomposed into a series of binary prospects. Then, the gains decomposition utility (gdu) of a prospect $(v_{\mathrm{P}}^{+}, p_{\mathrm{P}}; v_{\mathrm{P}}^{-}, p_{\$}; \dots ; v_n, p_n)$ with n payoffs could be denoted as

$$\text{gdu}(v_1, p_1; v_2, p_2; ...; v_n, p_n) = \sum_{j=0}^{n-1} \text{gdu}(v_1, p_1; ...; v_{n-j}, p_{n-j}) \left[1 - w\left(\frac{\sum_{i=1}^{n-j-1} p_i}{\sum_{i=1}^{n-j} p_i}\right)\right] \prod_{i=0}^{j-1} w\left(\frac{\sum_{k=1}^{n-i-1} p_k}{\sum_{k=1}^{n-i} p_k}\right), \quad \text{(I.9)}$$

where $w(p_i)$ is a probability weighting for p_i. According to the theory, gdu(P-bet) = $\text{w}(p_\text{P})v_\text{P}^+ + \text{w}(1 - p_\text{P})v_\text{P}^-$, where $\text{w}(p_\text{P}) = \frac{{p_\text{P}}^{0.542}}{[{p_\text{P}}^{0.542} + (1 - p_\text{P})^{0.542}]^{(1/0.542)}}$ and $\text{w}(1 - p_\text{P}) = \frac{(1 - p_\text{P})^{0.542}}{[(1 - p_\text{P})^{0.542} + {p_\text{P}}^{0.542}]^{(1/0.542)}}$ (cf., Figure I.28d).

Appendix I.4.2.4 Rank-dependent utility theory

Quiggin (1993) delineated rank-dependent utility (rdu) as an explanation for the Allais paradox without violating first-order stochastic dominance. A rank is represented by the probability of a prospect yielding a better payoff than a worse one. The rdu of a prospect is given by

$$\text{rdu}(v_1, p_\text{P}; v_2, p_2; ...; v_n, p_n) = \sum_{i=1}^{n}\left[w^+\left(\sum_{j=1}^{i} p_j\right) - w^+\left(\sum_{j=1}^{i-1} p_j\right)\right] u(v_i) + \sum_{i=1}^{n}\left[w^-\left(\sum_{j=1}^{i} p_j\right) - w^-\left(\sum_{j=1}^{i-1} p_j\right)\right] u(v_i), \quad \text{(I.10)}$$

where (1) $w^+(p_i)$ is a monotonically increasing function of probability weighting for positive outcomes $v_i \geqslant 0$; (2) $w^-(p_i)$ is a monotonically decreasing function of probability weighting for negative outcomes $v_i \leqslant 0$, both with boundary conditions $w^\pm(0) = 0$ and $w^\pm(1) = 1$; and (3) the function $u(v_i)$ is reserved for the utility of single payoff v_i only. According to the theory, rdu(P-bet) = $\mathrm{w}(p_{\mathrm{P}})v_{\mathrm{P}}^{+}$ + $\mathrm{w}(1 - p_{\mathrm{P}})v_{\mathrm{P}}^{-}$, where $\mathrm{w}(p_{\mathrm{P}}) = \frac{p_{\mathrm{P}}{}^{0.61}}{[p_{\mathrm{P}}{}^{0.61} + (1 - p_{\mathrm{P}})^{0.61}]^{(1/0.61)}}$, $\mathrm{w}(1 - p_{\mathrm{P}}) = \frac{(1 - p_{\mathrm{P}})^{0.61}}{[(1 - p_{\mathrm{P}})^{0.61} + p_{\mathrm{P}}{}^{0.61}]^{(1/0.61)}}$, $u(v_{\mathrm{P}}^{+}) = v_{\mathrm{P}}^{+0.88}$, and $u(v_{\mathrm{P}}^{-}) = \text{-}2.25(\text{-}v_{\mathrm{P}}^{-})^{0.88}$ (cf., Figure I.28d).

Appendix I.4.2.5 Subjectively weighted average utility theory

Karmarkar (1978) proposed subjectively weighted average utility (swau) model, a parsimonious extension to expected utility model. They differ with each other only in the way that probabilities are incorporated. The swau is given by

$$\text{swau}(v_1, p_1; v_2, p_2; ...; v_n, p_n) = \frac{\sum_{i=1}^{n} w(p_i)u(v_i)}{\sum_{i=1}^{n} w(p_i)}, \tag{I.11}$$

where $w(p_i)$ is a probability weighting for p_i, and the function $u(v_i)$ is reserved for the utility of single payoff v_i only. According to the theory, swau(P-bet) $= \frac{w(p_{\mathrm{P}})u(v_{\mathrm{P}}^{+}) + w(1 - p_{\mathrm{P}})u(v_{\mathrm{P}}^{-})}{w(p_{\mathrm{P}}) + w(1 - p_{\mathrm{P}})}$, where $\mathrm{w}(p_{\mathrm{P}}) = \frac{p_{\mathrm{P}}{}^{0.4}}{[p_{\mathrm{P}}{}^{0.4} + (1 - p_{\mathrm{P}})^{0.4}]^{(1/0.4)}}$, $\mathrm{w}(1 - p_{\mathrm{P}}) = \frac{(1 - p_{\mathrm{P}})^{0.4}}{[(1 - p_{\mathrm{P}})^{0.4} + p_{\mathrm{P}}{}^{0.4}]^{(1/0.4)}}$, $u(v_{\mathrm{P}}^{+}) = v_{\mathrm{P}}^{+0.4}$, and $u(v_{\mathrm{P}}^{-}) = (\text{-}v_{\mathrm{P}}^{-})^{0.4}$ (cf., Figure I.28e).

The above psychological transformations of objective probabilities and payoffs, p and v, into their subjective weights, w(p) and u(v), are depicted in Figure I.27 and Figure I.28, respectively.

While Table I.30 shows the deviations of price valuations from certainty equivalents for each benchmark theory, these results are broken down by loss or gain ratios (low vs. high) and treatment (not played-out vs. played-out but unpaied vs. incentives). On average, the participants over priced bets. There was not a significant "play-out" effect. The over pricing of both the P-bets and $-bets was most severe with no incentive-based, albeit played-out, treatment, most probably owing to the large magnitudes of MSRPs and EVs of those

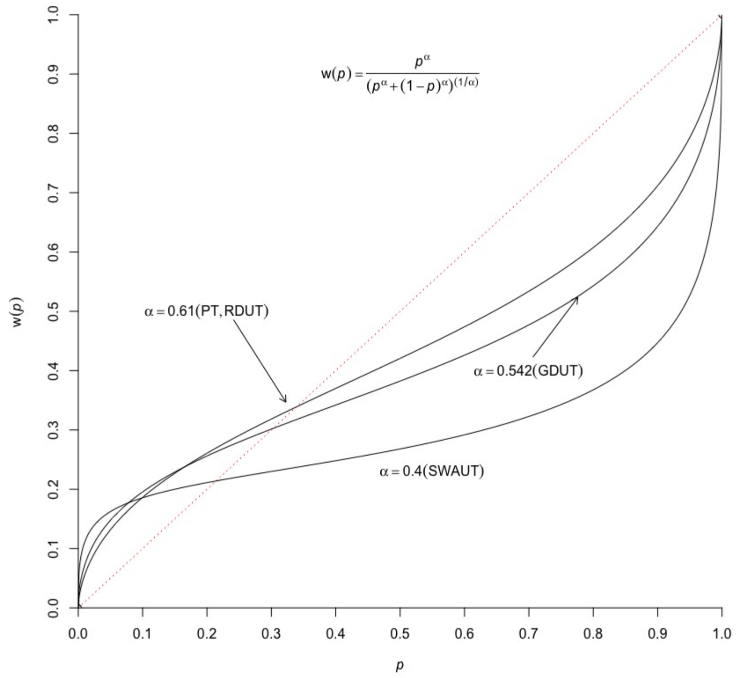
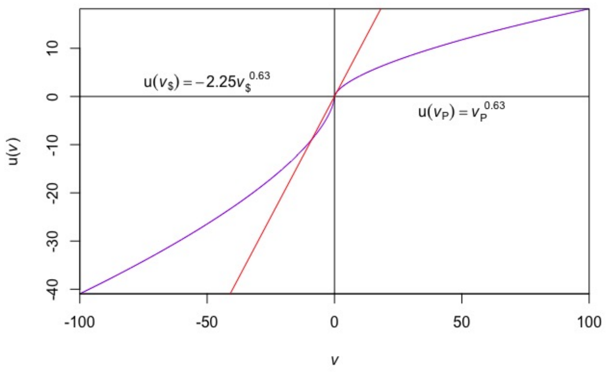


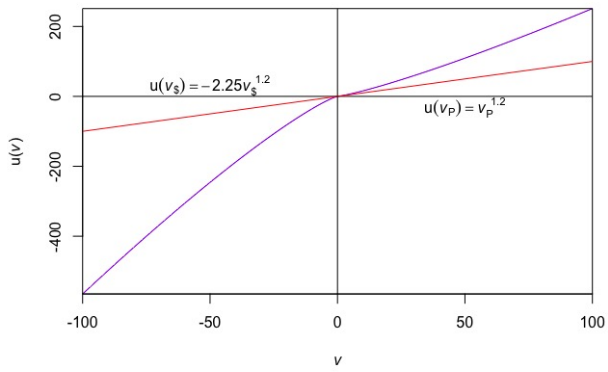
Figure I.27: Probability weight function w(p).
Note: PT: prospect theory; GDUT: (lower) gains decomposition utility theory; RDUT: rank-dependent utility theory; SWAUT: subjectively weighted average utility theory.

gambling options. However, there was a significant incentive effect for the \$-bets. The over pricing of the \$-bets was more severe under no incentive-based treatment than under incentive-based treatment.

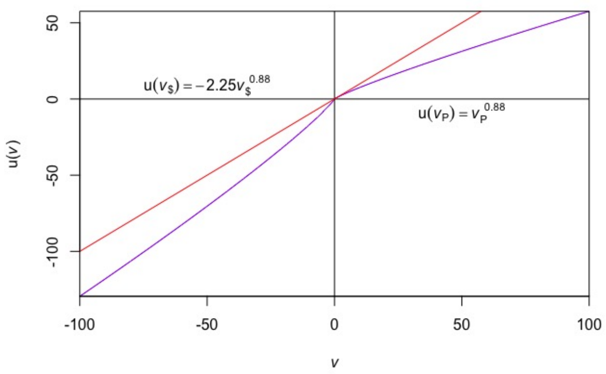
Moreover, expected utility theory (convex) was overall more accurate than the other benchmark theories for the P-bets, as evidenced (1) by the significances of over pricing which disappeared under the no incentive-based and no played-out treatment (all ps $>$ .600); and (2) by the magnitudes of over pricing which were the least severe (and least significant) under the no incentive-based, albeit played-out, treatment (all Ms $<$ 30.00 PLN and all ps $>$ .020). Once again, it should be noted that it is uncertain to what extent these treatments attributed in the findings, since our experiments that we compared here used considerably different designs and instructions.



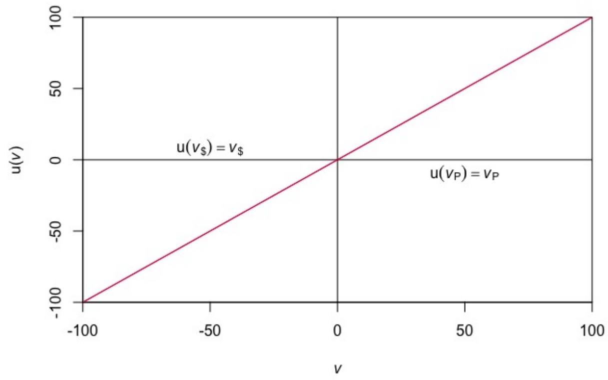
(a) Expected utility (concave)



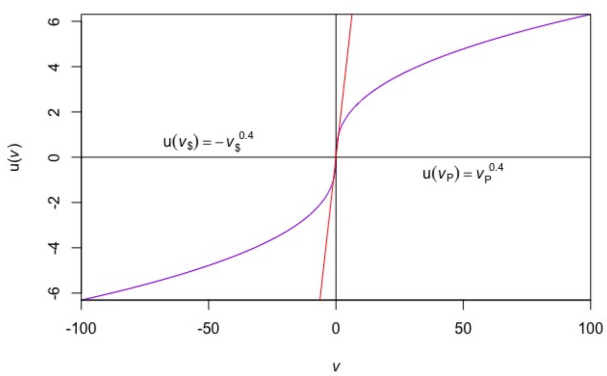
(b) Expected utility (convex)



(c) Prospect theory utility



(d) (Lower) gains decomposition utility and rank-dependent utility



(e) Subjectively weighted average utility

Figure I.28: Utility function $u(v)$.

Table I.30: Deviations from certainty equivalents by benchmark theories, low and high loss or gain ratios, and "play-out" and incentives treatments.

Benchmark theories	Loss/gain ratios	Item	Treatments[a] NP-NI P-bets	NP-NI $-bets	P-NI P-bets	P-NI $-bets	P-I[b] P-bets	P-I[b] $-bets	Tests of treatment effects P-bets		Tests of treatment effects $-bets	
EUT (concave)	Low	Observations	296	296	500	500	1,240	1,240				
		M	3.35	32.65	122.55	796.45	11.09	22.13	Kruskal-Wallis	289.28	Kruskal-Wallis	622.61
		95% CI	[2.53, 4.16]	[30.47, 34.82]	[90.54, 154.56]	[664.64, 928.26]	[10.54, 11.64]	[21.09, 23.16]	χ^2 Statistic		χ^2 Statistic	
		Robust T-Stat.	8.10***	29.57***	7.52***	11.87***	39.60***	41.98***	d.o.f.	2	d.o.f.	2
		p-value	< .001	< .001	< .001	< .001	< .001	< .001	p-value	< .001	p-value	< .001
		ξ	0.75	0.93	0.62	0.85	0.87	0.97				
	High	Observations	211	211	346	346	N/A	N/A				
		M	2.33	188.20	197.56	3,784.22			Wilcoxon rank	40,572.00	Wilcoxon rank	33,586.00
		95% CI	[1.42, 3.23]	[171.56, 204.83]	[145.34, 249.78]	[3,066.10, 4,502.33]			sum Statistic		sum Statistic	
		Robust T-Stat.	5.05***	22.31***	7.44***	10.37***			d.o.f.	1	d.o.f.	1
		p-value	< .001	< .001	< .001	< .001			p-value	< .001	p-value	< .001
		ξ	0.71	0.89	0.65	0.66						
	Total	Observations	647	647	846	846	1,240	1,240				
		M	2.88	61.73	149.94	1,336.21	11.09	22.13	Kruskal-Wallis	726.09	Kruskal-Wallis	1,787.90
		95% CI	[2.41, 3.36]	[56.27, 67.18]	[122.30, 177.57]	[1,158.98, 1,513.44]	[10.54, 11.64]	[21.09, 23.16]	χ^2 Statistic		χ^2 Statistic	
		Robust T-Stat.	11.89***	22.22***	10.65***	14.80***	39.60***	41.98***	d.o.f.	2	d.o.f.	2
		p-value	< .001	< .001	< .001	< .001	< .001	< .001	p-value	< .001	p-value	< .001
		ξ	0.75	0.99	0.64	0.84	0.87	0.97				

Table I.30: Deviations from certainty equivalents by benchmark theories, low and high loss or gain ratios, and “play-out” and incentives treatments. (continued)

Benchmark theories	Loss/gain ratios	Item	Treatments[a] NP-NI P-bets	NP-NI $-bets	P-NI P-bets	P-NI $-bets	P-I[b] P-bets	P-I[b] $-bets	Tests of treatment effects P-bets		$-bets	
	Low	Observations	296	296	500	500	1,240	1,240				
		M	-0.15	22.01	6.63	288.22	8.12	6.63	Kruskal-Wallis χ^2 Statistic	104.76	Kruskal-Wallis χ^2 Statistic	631.05
		95% CI	[-1.46, 1.17]	[19.44, 24.58]	[-2.10, 15.36]	[224.61, 351.83]	[7.45, 8.78]	[5.59, 7.67]				
		Robust T-Stat.	-0.22	16.87***	1.49	8.90***	24.06***	12.54***	d.o.f.	2	d.o.f.	2
		p-value	.824	$<$ .001	.136	$<$ .001	$<$ .001	$<$ .001	p-value	$<$ .001	p-value	$<$ .001
		ξ	0.02	0.86	0.91	0.63	0.78	0.66				
EUT (convex)	High	Observations	211	211	346	346	N/A	N/A				
		M	-0.58	198.94	28.44	3,205.87			Wilcoxon rank sum Statistic	82,886.00	Wilcoxon rank sum Statistic	34,520.00
		95% CI	[-2.81, -1.66]	[179.77, 218.12]	[2.83, 54.05]	[2,641.31, 3,770.44]						
		Robust T-Stat.	-0.51	20.45***	2.19*	11.17***			d.o.f.	1	d.o.f.	1
		p-value	.613	$<$ .001	.030	$<$ .001			p-value	$<$ .001	p-value	$<$ .001
		ξ	0.05	0.88	0.91	0.66						
	Total	Observations	647	647	846	846	1,240	1,240				
		M	0.24	53.59	11.80	798.22	8.12	6.63	Kruskal-Wallis χ^2 Statistic	142.06	Kruskal-Wallis χ^2 Statistic	1,584.30
		95% CI	[-0.73, 1.21]	[47.66, 59.53]	[1.57, 22.02]	[652.08, 944.37]	[7.45, 8.78]	[5.59, 7.67]				
		Robust T-Stat.	0.49	17.73***	2.27*	10.72***	24.06***	12.54***	d.o.f.	2	d.o.f.	2
		p-value	.624	$<$ .001	.024	$<$ .001	$<$ .001	$<$ .001	p-value	$<$ .001	p-value	$<$ .001
		ξ	0.03	0.94	0.71	0.64	0.78	0.66				

Table I.30: Deviations from certainty equivalents by benchmark theories, low and high loss or gain ratios, and "play-out" and incentives treatments. (continued)

Benchmark theories	Loss/gain ratios	Item	Treatments[a] NP-NI P-bets	NP-NI $-bets	P-NI P-bets	P-NI $-bets	P-I[b] P-bets	P-I[b] $-bets	Tests of treatment effects P-bets		Tests of treatment effects $-bets	
PT	Low	Observations	296	296	500	500	1,240	1,240				
		M	7.46	19.67	148.73	426.30	13.64	15.80	Kruskal-Wallis χ^2 Statistic	233.90	Kruskal-Wallis χ^2 Statistic	757.86
		95% CI	[6.42, 8.49]	[17.99, 21.35]	[111.94, 185.52]	[349.71, 502.90]	[13.07, 14.20]	[14.80, 16.80]				
		Robust T-Stat.	14.19***	23.03***	7.94***	10.94***	47.37***	30.94***	d.o.f.	2	d.o.f.	2
		p-value	< .001	< .001	< .001	< .001	< .001	< .001	p-value	< .001	p-value	< .001
		ξ	0.93	0.90	0.63	0.64	0.91	0.92				
	High	Observations	211	211	346	346	N/A	N/A				
		M	5.39	122.64	264.70	2,296.76			Wilcoxon rank sum Statistic	33,952.00	Wilcoxon rank sum Statistic	32,478.00
		95% CI	[4.12, 6.67]	[109.52, 135.76]	[192.93, 336.48]	[1,922.84, 2,670.69]						
		Robust T-Stat.	8.34***	18.43***	7.25***	12.08***			d.o.f.	1	d.o.f.	1
		p-value	< .001	< .001	< .001	< .001			p-value	< .001	p-value	< .001
		ξ	0.80	0.93	0.68	0.83						
	Total	Observations	647	647	846	846	1,240	1,240				
		M	6.26	40.70	185.57	852.84	13.64	15.80	Kruskal-Wallis χ^2 Statistic	727.53	Kruskal-Wallis χ^2 Statistic	1,634.40
		95% CI	[5.66, 6.86]	[36.77, 44.64]	[153.38, 217.76]	[719.79, 985.89]	[13.07, 14.20]	[14.80, 16.80]				
		Robust T-Stat.	20.40***	20.31***	11.31***	12.58***	47.37***	30.94***	d.o.f.	2	d.o.f.	2
		p-value	< .001	< .001	< .001	< .001	< .001	< .001	p-value	< .001	p-value	< .001
		ξ	0.91	0.95	0.65	0.66	0.91	0.92				

Table I.30: Deviations from certainty equivalents by benchmark theories, low and high loss or gain ratios, and "play-out" and incentives treatments. (continued)

Benchmark theories	Loss/gain ratios	Item	Treatments[a] NP-NI P-bets	NP-NI $-bets	P-NI P-bets	P-NI $-bets	P-I[b] P-bets	P-I[b] $-bets	Tests of treatment effects P-bets		Tests of treatment effects $-bets	
	Low	Observations	296	296	500	500	1,240	1,240				
		M	8.47	11.78	139.27	165.52	15.64	13.21	Kruskal-Wallis	214.18	Kruskal-Wallis	230.14
		95% CI	[7.22, 9.71]	[9.95, 13.61]	[103.97, 174.56]	[120.61, 210.42]	[15.00, 16.29]	[12.20, 14.22]	χ^2 Statistic		χ^2 Statistic	
		Robust T-Stat.	13.38***	12.66***	7.75***	7.24***	47.79***	25.70***	d.o.f.	2	d.o.f.	2
		p-value	< .001	< .001	< .001	< .001	< .001	< .001	p-value	< .001	p-value	< .001
		ξ	0.80	0.81	0.64	0.63	0.91	0.88				
GDUT	High	Observations	211	211	346	346	N/A	N/A				
		M	8.15	118.72	248.83	1256.57			Wilcoxon rank	38,073.00	Wilcoxon rank	48,189.00
		95% CI	[6.13, 10.17]	[105.24, 132.20]	[178.96, 318.71]	[1,002.59, 1,510.54]			sum Statistic		sum Statistic	
		Robust T-Stat.	7.96***	17.37***	7.01***	9.73***			d.o.f.	1	d.o.f.	1
		p-value	< .001	< .001	< .001	< .001			p-value	< .001	p-value	< .001
		ξ	0.77	0.89	0.68	0.66						
	Total	Observations	647	647	846	846	1,240	1,240				
		M	8.16	33.06	173.13	443.44	15.64	13.21	Kruskal-Wallis	613.00	Kruskal-Wallis	768.55
		95% CI	[7.28, 9.05]	[28.94, 37.18]	[143.50, 202.75]	[364.69, 522.20]	[15.00, 16.29]	[12.20, 14.22]	χ^2 Statistic		χ^2 Statistic	
		Robust T-Stat.	18.12***	15.75***	11.47***	11.05***	47.79***	25.70***	d.o.f.	2	d.o.f.	2
		p-value	< .001	< .001	< .001	< .001	< .001	< .001	p-value	< .001	p-value	< .001
		ξ	0.78	0.90	0.65	0.65	0.91	0.88				

Table I.30: Deviations from certainty equivalents by benchmark theories, low and high loss or gain ratios, and "play-out" and incentives treatments. (continued)

Benchmark theories	Loss/gain ratios	Item	Treatments[a] NP-NI P-bets	NP-NI $-bets	P-NI P-bets	P-NI $-bets	P-I[b] P-bets	P-I[b] $-bets	Tests of treatment effects P-bets		Tests of treatment effects $-bets	
RDUT	Low	Observations	296	296	500	500	1,240	1,240				
		M	13.00	25.37	264.57	492.76	18.94	17.42	Kruskal-Wallis χ^2 Statistic	308.64	Kruskal-Wallis χ^2 Statistic	823.21
		95% CI	[11.76, 14.24]	[23.33, 27.42]	[208.96, 320.18]	[404.50, 581.02]	[18.33, 19.55]	[16.43, 18.42]				
		Robust T-Stat.	20.57***	24.38***	9.35***	10.97***	60.89***	34.28***	d.o.f.	2	d.o.f.	2
		p-value	$< .001$	$< .001$	$< .001$	$< .001$	$< .001$	$< .001$	p-value	$< .001$	p-value	$< .001$
		ξ	0.89	0.91	0.97	0.97	0.92	0.93				
	High	Observations	211	211	346	346	N/A	N/A				
		M	12.52	167.58	462.00	2751.78			Wilcoxon rank sum Statistic	24,701.00	Wilcoxon rank sum Statistic	34,084.00
		95% CI	[10.78, 14.26]	[151.78, 183.39]	[356.07, 567.94]	[2,293.84, 3,209.71]						
		Robust T-Stat.	14.19***	20.90***	8.58***	11.82***			d.o.f.	1	d.o.f.	1
		p-value	$< .001$	$< .001$	$< .001$	$< .001$			p-value	$< .001$	p-value	$< .001$
		ξ	0.98	0.90	0.66	0.96						
	Total	Observations	647	647	846	846	1,240	1,240				
		M	12.11	51.85	330.33	957.84	18.94	17.42	Kruskal-Wallis χ^2 Statistic	913.02	Kruskal-Wallis χ^2 Statistic	1,737.90
		95% CI	[11.28, 12.93]	[46.89, 56.81]	[279.64, 381.02]	[807.77, 1,107.91]	[18.33, 19.55]	[16.43, 18.42]				
		Robust T-Stat.	28.93***	20.54***	12.79***	12.53***	60.89***	34.28***	d.o.f.	2	d.o.f.	2
		p-value	$< .001$	$< .001$	$< .001$	$< .001$	$< .001$	$< .001$	p-value	$< .001$	p-value	$< .001$
		ξ	0.93	0.95	0.62	0.67	0.92	0.93				

Table I.30: Deviations from certainty equivalents by benchmark theories, low and high loss or gain ratios, and "play-out" and incentives treatments. (continued)

			Treatments[a]									
			NP-NI		P-NI		P-I[b]		Tests of treatment effects			
Benchmark theories	Loss/gain ratios	Item	P-bets	$-bets	P-bets	$-bets	P-bets	$-bets	P-bets		$-bets	
		Observations	296	296	500	500	1,240	1,240				
		M	4.27	11.36	200.26	333.45	13.21	20.66	Kruskal-Wallis χ^2 Statistic	460.71	Kruskal-Wallis χ^2 Statistic	631.38
		95% CI	[3.47, 5.07]	[10.07, 12.64]	[156.59, 243.93]	[265.41, 401.49]	[12.66, 13.76]	[19.62, 21.69]				
	Low	Robust T-Stat.	10.52***	17.39***	9.01***	9.63***	47.25***	39.09***	d.o.f.	2	d.o.f.	2
		p-value	< .001	< .001	< .001	< .001	< .001	< .001	p-value	< .001	p-value	< .001
		ξ	0.74	0.84	0.60	0.63	0.90	0.95				
		Observations	211	211	346	346						
		M	4.55	17.60	348.01	846.53			Wilcoxon rank sum Statistic	28,109.00	Wilcoxon rank sum Statistic	24,340.00
		95% CI	[3.59, 5.51]	[14.65, 20.56]	[271.55, 424.48]	[678.95, 846.53]						
SWAUT	High	Robust T-Stat.	9.34***	11.74***	8.95***	9.94***	N/A	N/A	d.o.f.	1	d.o.f.	1
		p-value	< .001	< .001	< .001	< .001			p-value	< .001	p-value	< .001
		ξ	0.81	0.97	0.64	0.92						
		Observations	647	647	846	846	1,240	1,240				
		M	4.09	13.12	251.38	508.37	13.21	20.66	Kruskal-Wallis χ^2 Statistic	1,082.20	Kruskal-Wallis χ^2 Statistic	1,289.00
		95% CI	[3.58, 4.59]	[12.13, 14.10]	[211.81, 290.95]	[438.05, 578.70]	[12.66, 13.76]	[19.62, 21.69]				
	Total	Robust T-Stat.	15.81***	26.22***	12.47***	14.19***	47.25***	39.09***	d.o.f.	2	d.o.f.	2
		p-value	< .001	< .001	< .001	< .001	< .001	< .001	p-value	< .001	p-value	< .001
		ξ	0.85	0.95	0.98	0.65	0.90	0.95				

[a] NP or P indicate whether bets were Not Played-out or Played-out; NI or I indicate that No (monetary) Incentives were tied to bet payoffs or (monetary) Incentives were tied to bet payoffs (cf., Berg et al., 2013). M = 20% trimmed mean; ξ = explanatory measure of effect size (see Wilcox and Tian, 2011).
[b] The attraction decoy bets are excluded from analysis.
* $p < .05$; *** $p < .001$.