Bang for the Buck: Gain-Loss Ratio as a Driver of Judgment and Choice

Bart de Langhe, Stefano Puntoni

MANAGEMENT SCIENCE
Vol. 61, No. 5, May 2015, pp. 1137–1163
ISSN 0025-1909 (print) | ISSN 1526-5501 (online)

http://dx.doi.org/10.1287/mnsc.2014.2045

Bang for the Buck: Gain-Loss Ratio as a Driver of Judgment and Choice

Bart de Langhe
Leeds School of Business, University of Colorado, Boulder, Colorado 80309, bart.delanghe@colorado.edu

Stefano Puntoni
Rotterdam School of Management, Erasmus University, 3062 PA Rotterdam, The Netherlands, spuntoni@rsm.nl

Prominent decision-making theories propose that individuals (should) evaluate alternatives by combining gains and losses in an additive way. Instead, we suggest that individuals seek to maximize the rate of exchange between positive and negative outcomes and thus combine gains and losses in a multiplicative way. Sensitivity to gain-loss ratio provides an alternative account for several existing findings and implies a number of novel predictions. It implies greater sensitivity to losses and risk aversion when expected value is positive, but greater sensitivity to gains and risk seeking when expected value is negative. It also implies more extreme preferences when expected value is positive than when expected value is negative. These predictions are independent of decreasing marginal sensitivity, loss aversion, and probability weighting—three key properties of prospect theory. Five new experiments and reanalyses of two recently published studies support these predictions.

Keywords: gain-loss ratio; efficiency; decreasing marginal sensitivity; loss aversion; probability weighting; prospect theory; risk preference; mixed gambles
History: Received January 29, 2013; accepted June 26, 2014, by Yuval Rottenstreich, judgment and decision making. Published online in *Articles in Advance* December 3, 2014.

Life often confronts people with situations that can lead to positive and negative outcomes. Decisions involving some possibility of gain and loss range from the mundane (should I take a shorter but potentially more congested route to drive back from work?) to the consequential (should the government fund expensive new infrastructure that holds the promise of boosting the economy?). The judgment and decision-making literature refers to such situations as "mixed gambles." These are distinct from "single-domain gambles" that can only result in gains or only in losses. Mixed gambles are one of the most underexplored areas in judgment and decision-making research (Luce 2000, Wu et al. 2004). This dearth of research is problematic given the prevalence of such situations in real life and also surprising because some findings suggest that people process mixed gambles differently from single-domain gambles (Wu and Markle 2008).

The evaluation of a mixed gamble requires combining, or integrating, potential gains and losses. When both gains and losses are involved, applied disciplines often emphasize the rate of exchange between positive and negative outcomes—that is, efficiency. For example, managers care about return on investment when allocating resources to investment opportunities; health specialists are concerned with cost effectiveness ratios when funding health programs; and policy makers attend to benefit-cost ratios when allocating public funds. "Bang for the buck" is indeed a commonly heard expression in various contexts. In contrast, the judgment and decision-making literature has not considered the possibility that the ratio between positive and negative outcomes plays a role in how decision makers intuitively assess the utility of mixed gambles (for mixed gamble $L(g, p; l)$ yielding gain g with probability p and loss l with probability $(1-p)$, we define gain-loss ratio as $GLR = pg/[(1-p)(-l)]$). The goal of this paper is to explore this possibility and its implications.

1. Gain-Loss Ratio and Decision Making

Numerical quantities can be integrated in two general ways. Additive integration includes addition and subtraction (also called addition of the negative). Multiplicative integration includes multiplication and division (also called multiplication of the inverse). Most influential decision-theoretic models share the fundamental assumption that people integrate expected gains and losses using an additive rule (e.g., expected value (Pascal 1670/1966), expected utility theory (von Neumann and Morgenstern 1944), prospect theory (Kahneman and Tversky 1979)).[1]

The majority of existing empirical research in decision making involves single-domain gambles (Luce 2000, Wu et al. 2004). None of the problems presented in the original prospect theory paper by Kahneman and Tversky (1979), for instance, include gambles that can lead to both gains and losses. Previous research, however, suggests that conclusions from studies using single-domain gambles may not extend to mixed gambles (e.g., Wu and Markle 2008, Nilsson et al. 2011). For instance, Slovic et al. (2004) asked participants to rate either gamble L (\$9, 7/36; \$0) or gamble R(\$9, 7/36; −5¢) and find that gamble L is rated as less attractive than gamble R (on a scale from 0 to 20: 9.4 versus 14.9; see also Bateman et al. 2007, Peters et al. 2006). This result seems to violate the assumption of additive integration of gains and losses and it is thus hard to explain based on the dominant models of decision making. Slovic et al. (2004, p. 317) propose that "the combination of a possible \$9 gain and a 5¢ loss is a very attractive win/lose ratio, leading to a relatively precise mapping onto the upper part of the scale. Whereas the imprecise mapping of the \$9 carries little weight in the averaging process, the more precise and now favorable impression of (\$9 − 5¢) carries more weight, thus leading to an increase in the overall favorability of the gamble." Although this account is ambiguous as to whether people use a multiplicative ("win/lose ratio") or an additive ("\$9 − 5¢") integration rule, it suggests that the cognitive operations involved when people evaluate gains and losses in the context of mixed gambles may differ from those involved in the evaluation of single-domain gambles.

Although gain-loss ratio reasoning has not been considered in theories of human decision making under risk, decision scientists have documented the importance of proportional reasoning in a variety of other settings, including intertemporal choice (Read et al. 2013), preference reversals (Hsee 1998), judgments of savings (Bartels 2006), choice in two-part bets (Anderson and Shanteau 1970), and unidimensional difference judgments (Wright 2001). Sensitivity to gain-loss ratio in decision making under risk would be another instance of proportional thinking. The central claim of this paper is that, when evaluating mixed gambles, people tend to focus on whether the gambles offer an efficient return of positive resources in exchange for negative resources and thus tend to favor gambles with larger gain-loss ratios. This basic contention has a number of specific implications, which we derive next.

1.1. Expected Monetary Value

To maximize monetary outcomes, people should favor decision options with higher expected value. A mixed gamble that dominates another in terms of gain-loss ratio often also dominates it in terms of expected value. Consider, for example, gambles $L(20, 0.5; -5)$ and $R(30, 0.5; -20)$. Choosing gamble L over gamble R maximizes gain-loss ratio ($GLR_L = 4 > GLR_R = 1.5$) as well as expected value ($EV_L = 7.5 > EV_R = 5$). The correlation between gain-loss ratio and expected value is, however, far from perfect. Consider, for example, gambles $L(20, 0.5; -5)$ and $S(40, 0.5; -20)$. Choosing gamble L over gamble S maximizes gain-loss ratio ($GLR_L = 4 > GLR_S = 2$) but not expected value ($EV_L = 7.5 < EV_S = 10$). Thus, there exists a region in the outcome space where gain-loss ratio favors one option whereas expected value favors the other. Maximizing gain-loss ratio leads to choosing the option with the higher expected value when gain-loss ratio and expected value are aligned but to choosing the option with the lower expected value when gain-loss ratio and expected value are not aligned. Appendix A formally determines the areas of the outcome space where gain-loss ratio and expected value are dissociated, and Figure 1 provides a geometric representation of these arguments.

Hypothesis 1A (H1A). *Decision makers favor gambles with higher monetary outcomes when gain-loss ratio and expected value are aligned.*

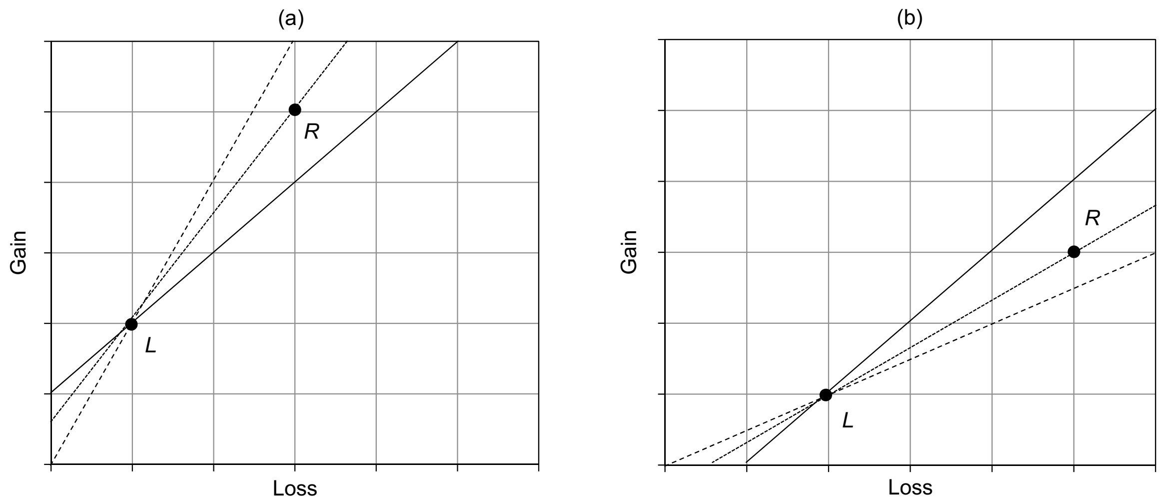
Hypothesis 1B (H1B). *Decision makers favor gambles with lower monetary outcomes when gain-loss ratio and expected value are dissociated.*

1.2. Risk Preferences

For gambles with positive expected value, gain-loss ratio is influenced more by variation in losses than by equal variation in gains. Consider, for instance gamble $L(20, 0.5; -5)$ with positive expected value. Increasing both the gain and loss portions of gamble L with 10 yields a more risky gamble $R(30, 0.5; -15)$ with equal expected value ($EV_L = EV_R = 7.5$) but lower gain-loss ratio ($GLR_L = 4 > GLR_R = 2$). Maximizing gain-loss ratio thus implies choosing gamble L with lower outcome variance over gamble R with higher outcome variance—or, risk aversion.

[1] Heuristic models of decision making under risk do not assume additive integration of expected outcomes. For example, Brandstatter et al. (2006) found the priority heuristic to be the best predictor of choice between single-domain gambles. Although the priority heuristic was not specifically developed for this purpose, the authors discuss a possible extension to the case of mixed gambles. Accordingly, choice should be based on a comparison of the difference in losses with 1/10th of the highest gain rounded to the next prominent number. We conducted additional analyses for all choice studies reported in this paper. Predictions based on the priority heuristic are not confounded with predictions based on gain-loss ratio. Moreover, the predictive validity of the priority heuristic is often lower than that of prospect theory and expected value theory.

Figure 1 **Implications of Sensitivity to Gain-Loss Ratio for Monetary Outcomes and Risk Preference (See Appendix A)**



Notes. In both (a) and (b), the dashed line indicates all gambles in the outcome space with the same gain-loss ratio as gamble L, the solid line indicates all gambles in the outcome space with the same expected value as gamble L, and the dotted line relates gamble L to any gamble R in the outcome space. (a) When choosing between gambles with positive expected value, reliance on gain-loss ratio leads to suboptimal monetary outcomes whenever the slope of the dotted line is less steep than the gain-loss ratio indifference line but steeper than the expected value indifference line. In the positive domain, the slope of the gain-loss ratio indifference line is steeper than the expected value indifference line, implying risk aversion when choice is based on gain-loss ratio. (b) When choosing between gambles with negative expected value, reliance on gain-loss ratio leads to suboptimal monetary outcomes whenever the slope of the dotted line is steeper than the gain-loss ratio indifference line but less steep than the expected value indifference line. In the negative domain, the slope of the gain-loss ratio indifference line is less steep than the expected value indifference line, implying risk seeking when choice is based on gain-loss ratio.

For gambles with negative expected value, instead, gain-loss ratio is influenced more by variation in gains than by equal variation in losses. Consider, for instance, gamble $L'(5, 0.5; -20)$ with negative expected value. Increasing both the gain and loss portions of gamble L' with 10 yields a more risky gamble $R'(15, 0.5; -30)$ with equal expected value ($EV_{L'} = EV_{R'} = -7.5$) but higher gain-loss ratio ($GLR_{L'} = 0.25 < GLR_{R'} = 0.5$). Maximizing gain-loss ratio thus implies choosing gamble R' with higher outcome variance over gamble L' with lower outcome variance—or, risk seeking. Appendix B presents a formal derivation for the predictions of risk aversion in the positive expected value domain and risk seeking in the negative expected value domain (see also Figure 1).

Hypothesis 2A (H2A). *Decision makers favor less risky gambles when expected value is positive.*

Hypothesis 2B (H2B). *Decision makers favor more risky gambles when expected value is negative.*

The prediction of risk seeking for mixed gambles with negative expected value is especially interesting because it is inconsistent with expected utility theory according to which people should minimize outcome variance (i.e., risk) for a given average outcome (i.e., expected value) regardless of whether expected value is positive or negative. It is also inconsistent with modern portfolio theory (Markowitz 1952), the standard risk management framework used in finance, which aims at minimizing risk for a given level of expected return.[2] Finally, it runs counter to prospect theory's principle of loss aversion according to which variation in losses should be weighted more than equal variation in gains implying risk aversion for mixed gambles (e.g., Thaler et al. 1997).

1.3. Preference Extremity

If people are sensitive to gain-loss ratio, it follows that the perceived attractiveness of two mixed gambles should differ less when gain-loss ratio is not diagnostic than when it is diagnostic (i.e., when gain-loss ratio does not favor versus does favor one of the two gambles). In other words, choice shares for two mixed gambles should differ less when gain-loss ratio is equal than when gain-loss ratio is unequal.

Hypothesis 3 (H3). *Preferences are less extreme when gain-loss ratio is not diagnostic.*

Reliance on gain-loss ratio also implies that preference extremity is asymmetric across the two expected value domains (positive versus negative). Gain-loss ratio can vary between 1 and $+\infty$ for gambles with positive expected value but is instead compressed between 0 and 1 for gambles with negative expected value. Increasing the gain and loss portions of a

[2] It can be shown that the ranking of a set of gambles based on their means and variances is the same as their ranking based on expected utility theory with a standard concave utility function over wealth (Levy and Markowitz 1979, Meyer 1987).

gamble by adding the same constant will in absolute terms have a smaller impact on gain-loss ratio when expected value is negative than when expected value is positive. Thus, if people are sensitive to gain-loss ratio they should find it harder to discriminate between gambles with negative expected value. To illustrate, consider gambles $L(20, 0.5; -5)$ and $R(30, 0.5; -15)$ that only differ by a constant (increase the gain and loss portions of gamble L by 10 to obtain gamble R). Gamble R has a lower gain-loss ratio than gamble $L(GLR_R - GLR_L = 2 - 4 = -2)$. Now consider gambles $L'(5, 0.5; -20)$ and $R'(15, 0.5; -30)$ that are identical to the previous gamble pair except for inverted gain and loss portions. Gambles L' and R' also differ only by a constant (increase the gain and loss portions of gamble L' by 10 to obtain gamble R'). Gamble R' has a higher gain-loss ratio than gamble $L'(GLR_{R'} - GLR_{L'} = 0.5 - 0.25 = 0.25)$. Crucially, the absolute change in gain-loss ratio after adding the constant is smaller when expected value is negative ($|GLR_{R'} - GLR_{L'}| = 0.25$) than when it is positive ($|GLR_R - GLR_L| = 2$). In sum, sensitivity to gain-loss ratio implies less extreme preferences when gambles have negative expected value. Moreover, if the effect of expected value domain on preference extremity can be traced to the discriminability of gain-loss ratios, this effect should be mediated by the difference in the gambles' gain-loss ratios.

Hypothesis 4 (H4). *Preferences are less extreme when expected value is negative.*

Hypothesis 5 (H5). *The effect of expected value domain on preference extremity is mediated by gain-loss ratio differences.*

In addition, if people find it harder to discriminate between mixed gambles when expected value is negative than when expected value is positive, we should also observe an effect of expected value domain on process measures of deliberation. When two stimuli are more similar on a dimension people tend to be less confident about their ability to discriminate between the stimuli using that dimension and they take longer to decide (Cartwright 1941, Festinger 1943). Decision time thus gives an indication of the dimension that participants attend to when comparing two stimuli. If people compare gambles based on gain-loss ratio, decision time should be longer when expected value is negative than when expected value is positive because the difference in gain-loss ratio between gambles is smaller when expected value is negative.

Hypothesis 6 (H6). *Decision time is longer when expected value is negative.*

Hypothesis 7 (H7). *The effect of expected value domain on decision time is mediated by gain-loss ratio differences.*

1.4. Prospect Theory

Given the prominence of prospect theory (Kahneman and Tversky 1979) in the judgment and decision-making literature, we pay special attention to it here and analyze whether prospect theory can provide an alternative account for gain-loss ratio maximization. According to prospect theory, gains and losses are evaluated by a value function characterized by the properties of loss aversion (i.e., losses loom larger than corresponding gains) and diminishing sensitivity (i.e., the marginal value of gains and losses decreases with their size). These properties give rise to an asymmetric S-shaped value function, steeper for gains than for losses, and concave for gains but convex for losses. Probabilities are evaluated by a weighting function that overweights small probabilities and underweights large probabilities, implying an inverse S-shaped probability weighting function.

Formally, the value V of a gamble $L = (g, p; l)$ is determined as follows: $V = \pi(p)v(g) + \pi(1-p)v(l)$, where $v(\cdot)$ is a value function over gains and losses such that $v(g) = g^{\alpha}$ and $v(l) = -\lambda(-l)^{\beta}$ and $\pi(\cdot)$ is a probability weighting function such that $\pi(p) = p^{\gamma}/[p^{\gamma} + (1-p)^{\gamma}]^{1/\gamma}$. The λ parameter indicates how losses are weighted relative to gains. Losses are weighted more than gains if $\lambda > 1$. The α and β parameters indicate the curvature in the value function. The value function is more concave (linear) for gains as α approaches zero (one) and more convex (linear) for losses as β approaches zero (one). The parameter estimates for the value function returning most often in the literature are the ones provided by Tversky and Kahneman (1992). They estimated α and β at 0.88 and λ at 2.25. Wu and Markle (2008) estimated that for mixed gambles the γ parameter in the probability weighting function is 0.55.

With its many free parameters, prospect theory can fit numerous data sets very well and can easily mimic predictions made by other choice models. To explore which estimates would be obtained for prospect theory parameters if people made decisions that maximize gain-loss ratio, we conducted a simulation study. Specifically, we generated a data set with gamble pairs randomly sampled from an outcome space and determined expected choice shares following gain-loss ratio maximization. We then estimated prospect theory parameters based on this data set. Appendix C presents the procedures and conclusions for this simulation study in detail, but we present the main takeaways here. As expected, prospect theory can fit the data very well, but the parameter estimates deviate from those appearing most commonly in the literature. First, the loss-aversion parameter λ ranges between 1 and 1.70. Second, the estimated values for α and β lie close to 0 indicating extreme curvature in the value function. In other words, choice based on a comparison of gain-loss ratios implies parameter estimates that would suggest loss aversion and decreasing marginal sensitivity, even in the absence of actual loss aversion and diminishing sensitivity. In our empirical studies we will estimate prospect theory parameters and compare parameter estimates to those obtained in the simulation study.

1.5. Summary

In sum, we propose that individuals tend to favor mixed gambles with larger gain-loss ratios. This tendency implies the following:

- Decision makers should favor gambles with higher monetary outcomes when gain-loss ratio and expected value are aligned (H1A) but gambles with lower monetary outcomes when gain-loss ratio and expected value are dissociated (H1B).
- Decision makers should favor gambles with smaller outcome magnitudes when expected value is positive (H2A) but gambles with larger outcome magnitudes when expected value is negative (H2B).
- Choice shares should be less extreme when gain-loss ratio is not diagnostic (H3).
- Choice shares should be less extreme when gain-loss ratio is negative (H4) because differences between gambles in terms of gain-loss ratio are smaller when expected value is negative (H5).
- Decision times should be longer when expected value is negative (H6) because differences between gambles in terms of gain-loss ratio are smaller when expected value is negative (H7).

We report five new studies and two reanalyses of previously published data that test these hypotheses in both joint- and single-evaluation contexts, focusing, respectively, on choice and ratings of attractiveness. Table 1 provides a summary of the hypotheses including a description of the type of evidence that would support each of them as well as a reference to the relevant studies.

2. Study 1

Study 1 examines all hypotheses using a data set of over 5,000 choices for 260 pairs of mixed gambles. All gambles had equal probability of winning and losing. This feature of the study design allows us to abstract from the probability weighting function when estimating prospect theory parameters. This is important because the curvature in the value function is not identified uniquely from the curvature of the probability weighting function (Prelec 1998, Wu and Markle 2008). Although we acknowledge that gambles with equal probability of winning and losing are only a subset of all possible mixed gambles, in many real-life situations gains and losses are equally possible. Moreover, even when probabilities are unequal, people often ignore them. For example, managers interviewed by March and Shapira (1987, p. 1407) indicated that they "don't look at the probability of success or failure" but rather to the magnitude of outcomes. More formally, Wu and Markle (2008) presented single-domain and mixed gambles to participants in a lab context and found that probabilities are

Table 1 Hypotheses

Number	Description	Studies	Example data
H1A	Preference for gambles with higher expected value when gain-loss ratio and expected value are aligned	1, 4, 6	Prefer (20, 0.5; −5) over (30, 0.5; −20)
H1B	Preference for gambles with lower expected value when gain-loss ratio and expected value are dissociated	1, 4, 6	Prefer (20, 0.5; −5) over (40, 0.5; −20)
H2A	Risk aversion when expected value is positive	1, 2, 3, 4, 5	Prefer (20, 0.5; −5) over (30, 0.5; −15)
H2B	Risk seeking when expected value is negative	1, 3, 5, 6, 7	Prefer (15, 0.5; −30) over (5, 0.5; −20)
H3	Less extreme preferences when gain-loss ratio is not diagnostic	1, 4	Choice shares are closer to 0.5 when choosing between (20, 0.5; −10) and (40, 0.5; −20) than when choosing between (30, 0.5; −10) and (40, 0.5; −20)
H4	Less extreme preferences when expected value is negative versus positive	1, 3, 5	Choice shares are closer to 0.5 when choosing between (5, 0.5; −20) and (15, 0.5; −30) than when choosing between (20, 0.5; −5) and (30, 0.5; −15)
H5	H4 is mediated by differences in gain-loss ratio	1	H4 occurs because the difference in gain-loss ratio between (5, 0.5; −20) and (15, 0.5; −30) is smaller than the difference in gain-loss ratio between (20, 0.5; −5) and (30, 0.5; −15), that is, 0.25 is smaller than 2
H6	Longer decision times when expected value is negative versus positive	1	Deliberate longer when choosing between (5, 0.5; −20) and (15, 0.5; −30) than when choosing between (20, 0.5; −5) and (30, 0.5; −15)
H7	H6 is mediated by differences in gain-loss ratio	1	H6 occurs because the difference in gain-loss ratio between (5, 0.5; −20) and (15, 0.5; −30) is smaller than the difference in gain-loss ratio between (20, 0.5; −5) and (30, 0.5; −15), that is, 0.25 is smaller than 2

less influential when choosing between mixed gambles. We believe that mixed gambles with equal probability of winning and losing therefore mimic how many real-life situations are mentally reconstructed. However, we will explore the role of probabilities in Studies 5–7.

2.1. Method

2.1.1. Participants, Design, and Procedure. Two hundred seventy-three business undergraduates at a European university participated in this study in exchange for extra course credit (127 females, $M_{\text{age}} = 20.96$, $SD = 2.65$). Participants completed the study in individual cubicles and were asked to choose 20 times between two gambles offering an equal probability of winning and losing. Response time for each decision was measured unobtrusively. Data from four participants were eliminated before performing the analyses (three of them took on average less than one second per decision and one always clicked on the left response button), leading to a final sample size of 269. The gambles were sampled (without replacement) from an outcome space with gains and losses ranging from €5 to €30 with increments of €5. We randomly assigned participants to choose between gambles with either positive or negative expected value. One hundred thirty-seven participants were presented with 20 gamble pairs with positive expected value, whereas the others were presented with 20 gamble pairs with negative expected value. This manipulation allows testing hypotheses H4–H7 pertaining to preference extremity. In total, the data set consists of 5,380 decisions.

2.1.2. Sampling Procedure. For each participant, 20 gamble pairs were randomly sampled from the outcome space, subject to three restrictions:

- the expected value of the gambles was not zero (that is, the gain was never equal to the loss);
- the gain portions varied across gambles (that is, gains were never equal);
- the loss portions varied across gambles (that is, losses were never equal).

After applying these restrictions, 260 unique gamble pairs remained. Note that two gambles were coded as a different gamble pair if the order in which the two gambles was displayed differed (left versus right side of the screen). Half of these gamble pairs had a positive expected value and the other half had a negative expected value. Tables 2(a) and 2(b) illustrate the design of this study for gamble pairs with positive and negative expected value, respectively.

Participants were presented with four types of gamble pairs. The first category (140 gamble pairs) consists of gamble pairs for which gain-loss ratio and expected value favor the same option. The second category (20 gamble pairs) consists of gambles for which gain-loss ratio and expected value are dissociated. If gain-loss ratio drives choice, participants will incur suboptimal monetary outcomes when presented with gamble pairs from category 2 but not when presented with gamble pairs from category 1 (H1). The third category (80 gamble pairs) consists of gambles with equal expected value. This category affords a clean test of participants' preference for risk (H2). Holding constant expected value, risk aversion implies choosing the gamble with lower outcome variance. Risk seeking implies choosing the gamble with higher outcome variance. The fourth category (20 gamble pairs) consists of gambles with equal gain-loss ratio. If gain-loss ratio is an important determinant of choice, choice shares should be less extreme when gain-loss ratio is equal (H3). Every participant was presented with five gamble pairs sampled from each of the categories above.

2.2. Results

For each of the 5,380 choices, gain-loss ratio makes a prediction (i.e., "choose gamble *L*," "choose gamble *R*," "choose gamble *L* or gamble *R*"). The accuracy of gain-loss ratio was scored as 1 if gain-loss ratio accurately predicted choice and as 0 if gain-loss ratio did not accurately predict choice. Accuracy was scored as a missing value if gain-loss ratio was not diagnostic for the particular gamble pair (i.e., choose gamble *L* or gamble *R*). We averaged accuracy scores for each of the 240 gamble pairs for which gain-loss ratio makes a prediction and then we averaged again across gamble pairs to obtain an overall accuracy index. This is the most precise estimate of the general accuracy of gain-loss ratio in this outcome space because the score obtained by directly averaging across the 5,380 choices would disproportionately weight some gambles relative to others (because of our sampling procedure). Gain-loss ratio accurately predicted choice 82% of the times ($SD = 0.17$). This high level of accuracy is consistent with our arguments about the importance of gain-loss ratio in decision making. Consistent with our predictions pertaining to gain-loss ratio discriminability (H4–H7), gain-loss ratio predicts choice more accurately when expected value is positive than when expected value is negative (85% versus 79%, $t(238) = 2.97$, $p < 0.001$). We explore the impact of gain-loss ratio discriminability in more detail below.

2.2.1. Expected Monetary Value (H1). Gain-loss ratio and expected value favor the same option for 140 of the 260 gamble pairs (see category 1 above). The likelihood of choosing the gamble with the higher expected value averaged across these pairs is significantly higher than chance ($M = 0.91$, $SD = 80.11$, $t(139) = 42.69$, $p < 0.001$). Thus, in support of H1A, when two gambles are ranked the same based on expected value and gain-loss ratio, people favor the

Table 2 **Design and Results of Study 1**

A. Gamble pairs with positive expected value

Gamble *L*	Gamble *R*	(30; −25)	(30; −20)	(30; −15)	(30; −10)	(30; −5)	(25; −20)	(25; −15)	(25; −10)	(25; −5)	(20; −15)	(20; −10)	(20; −5)	(15; −10)	(15; −5)	(10; −5)
	GLR *EV*	1.2 2.5	1.5 5	2 7.5	3 10	6 12.5	1.25 2.5	1.67 5	2.5 7.5	5 10	1.33 2.5	2 5	4 7.5	1.5 2.5	3 5	2 2.5
(30; −25)	1.2 2.5	X	X	X	X	X	16.67 (12)	0.00 (5)	0.00 (9)	14.29 (7)	26.67 (15)	22.22 (9)	7.14 (14)	11.77 (17)	14.29 (7)	23.08 (13)
(30; −20)	1.5 5	X	X	X	X	X	X	26.32 (19)	12.50 (8)	0.00 (9)	80.00 (10)	17.65 (17)	0.00 (9)	49.28 (69)	9.52 (21)	25.00 (64)
(30; −15)	2 7.5	X	X	X	X	X	1.00 (12)	X	38.10 (21)	11.11 (9)	X	66.25 (80)	0.00 (15)	90.91 (11)	50.00 (68)	60.61 (66)
(30; −10)	3 10	X	X	X	X	X	90.00 (10)	90.91 (11)	X	15.00 (20)	1.00 (10)	X	23.88 (67)	X	65.63 (64)	71.43 (7)
(30; −5)	6 12.5	X	X	X	X	X	1.00 (9)	1.00 (9)	90.91 (11)	X	1.00 (9)	83.33 (6)	X	1.00 (8)	X	X
(25; −20)	1.25 2.5	56.25 (16)	X	0.00 (6)	0.00 (10)	0.00 (12)	X	X	X	X	31.25 (16)	7.14 (14)	0.00 (8)	29.63 (27)	16.67 (6)	20.00 (20)
(25; −15)	1.67 5	88.89 (9)	68.42 (19)	X	0.00 (13)	8.33 (12)	X	X	X	X	X	41.18 (17)	0.00 (3)	63.64 (11)	10.53 (19)	38.10 (63)
(25; −10)	2.5 7.5	83.33 (12)	92.31 (13)	73.33 (15)	X	0.00 (4)	X	X	X	X	1.00 (7)	X	22.22 (18)	X	41.27 (63)	91.67 (12)
(25; −5)	5 10	90.91 (11)	90.91 (11)	77.78 (9)	93.75 (16)	X	X	X	X	X	1.00 (10)	90.00 (10)	X	1.00 (6)	X	X
(20; −15)	1.33 2.5	85.71 (14)	55.56 (9)	X	0.00 (16)	12.50 (16)	66.67 (18)	X	0.00 (9)	0.00 (10)	X	X	X	35.29 (17)	16.67 (6)	14.29 (14)
(20; −10)	2 5	1.00 (10)	82.35 (17)	38.60 (57)	X	0.00 (9)	1.00 (6)	80.95 (21)	X	0.00 (11)	X	X	X	X	21.74 (23)	50.60 (83)
(20; −5)	4 7.5	77.78 (9)	1.00 (9)	86.36 (22)	72.86 (70)	X	1.00 (13)	1.00 (17)	81.82 (11)	X	X	X	X	1.00 (14)	X	X
(15; −10)	1.5 2.5	89.47 (19)	45.59 (68)	0.00 (6)	X	0.00 (15)	60.00 (15)	22.22 (9)	X	0.00 (12)	92.86 (14)	X	0.00 (4)	X	X	30.77 (13)
(15; −5)	3 5	66.67 (9)	75.00 (16)	71.01 (69)	30.14 (73)	X	100.00 (9)	76.47 (17)	59.46 (74)	X	92.86 (14)	78.57 (14)	X	X	X	X
(10; −5)	2 2.5	80.00 (20)	69.86 (73)	47.89 (71)	26.67 (15)	X	78.57 (14)	66.22 (74)	50.00 (10)	X	85.60 (10)	35.19 (54)	X	89.47 (19)	X	X

Table 2 (Continued)

	B. Gamble pairs with negative expected value															
	Gamble *R*	(25; −30)	(20; −30)	(15; −30)	(10; −30)	(5; −30)	(20; −25)	(15; −25)	(10; −25)	(5; −25)	(15; −20)	(10; −20)	(5; −20)	(10; −15)	(5; −15)	(5; −10)
Gamble *L*	*GLR* *EV*	0.83 −2.50	0.67 −5	0.5 −7.5	0.33 −10	0.17 −12.5	0.8 −2.5	0.6 −5	0.4 −7.5	0.2 −10	0.75 −2.5	0.5 −5	0.25 −7.5	0.67 −2.5	0.33 −5	0.5 −2.5
(25; −30)	0.83 −2.5	X	X	X	X	X	44.44 (18)	84.62 (13)	100 (9)	80.00 (5)	47.37 (19)	60.00 (10)	92.31 (13)	47.06 (17)	76.92 (13)	82.35 (17)
(20; −30)	0.67 −5	X	X	X	X	X	X	50.00 (14)	77.78 (9)	81.82 (11)	33.33 (6)	50.00 (20)	75.00 (8)	25.71 (70)	66.67 (18)	52.54 (59)
(15; −30)	0.5 −7.5	X	X	X	X	X	12.50 (8)	X	56.25 (16)	87.50 (8)	X	27.54 (69)	95.00 (20)	8.33 (12)	48.68 (76)	25.00 (64)
(10; −30)	0.33 −10	X	X	X	X	X	0.00 (11)	10.00 (10)	X	66.67 (15)	7.14 (14)	X	51.67 (60)	X	16.18 (68)	0.00 (13)
(5; −30)	0.17 −12.5	X	X	X	X	X	0.00 (11)	0.00 (7)	8.33 (12)	X	11.11 (9)	0.00 (3)	X	25.00 (4)	X	X
(20; −25)	0.8 −2.5	43.75 (16)	X	100 (4)	92.86 (14)	100	X	X	X	X (18)	50.00 (4)	100 (10)	100 (8)	66.67 (12)	90.91 (11)	55.00 (20)
(15; −25)	0.6 −5	12.50 (8)	41.67 (12)	X	100 (8)	100 (13)	X	X	X	X	X	61.91 (21)	90.00 (10)	16.67 (6)	90.00 (10)	38.46 (65)
(10; −25)	0.4 −7.5	0.00 (7)	22.22 (9)	23.08 (13)	X	100 (11)	X	X	X	X	0.00 (8)	X	27.72 (22)	X	39.71 (68)	27.27 (11)
(5; −25)	0.2 −10	7.14 (14)	0.00 (8)	0.00 (5)	27.78 (18)	X	X	X	X	X	0.00 (10)	0.00 (15)	X	0.00 (11)	X	X
(15; −20)	0.75 −2.5	70.59 (17)	77.78 (9)	X	100 (11)	100 (10)	35.00 (20)	X	88.89 (9)	100 (8)	X	X	X	72.22 (18)	84.61 (13)	73.33 (15)
(10; −20)	0.5 −5	18.18 (11)	30.00 (10)	80.95 (63)	X	87.50 (8)	0.00 (4)	80.00 (15)	X	100 (4)	X	X	X	X	84.62 (13)	31.17 (77)
(5; −20)	0.25 −7.5	22.22 (9)	12.50 (8)	21.43 (14)	43.06 (72)	X	0.00 (9)	10.00 (10)	0.00 (9)	X	X	X	X	7.69 (13)	X	X
(10; −15)	0.67 −2.50	52.94 (17)	69.36 (62)	100 (11)	X	100 (14)	5.00 (20)	83.33 (12)	X	85.71 (7)	52.38 (21)	X	100 (7)	X	X	80.00 (15)
(5; −15)	0.33 −5	0.00 (13)	23.53 (17)	51.79 (56)	78.13 (64)	X	37.50 (8)	15.00 (20)	60.94 (64)	X	37.50 (8)	25.00 (12)	X	X	X	X
(5; −10)	0.5 −2.5	37.50 (16)	53.43 (73)	77.94 (68)	91.67 (12)	X	42.86 (14)	50.75 (67)	87.50 (8)	X	35.00 (20)	72.73 (55)	X	28.57 (21)	X	X

Notes. The first column and row indicate the payoffs of gambles presented on the left (gamble *L*) and right (gamble *R*). Probabilities of winning and losing were equal to 0.5 for all gambles. The second column and row indicate the gambles' gain-loss ratio (first line) and expected value (second line). The numbers in the remaining cells indicate the percentage of participants choosing for gamble *L* and between parentheses the number of participants that were presented with the gamble pair. The X symbols indicate gambles disqualified based on sampling restrictions.

gamble with higher expected monetary value. Gain-loss ratio and expected value are dissociated for 20 of the 260 gamble pairs (see category 2 above). The likelihood of choosing the gamble with the higher expected value (and thus lower gain-loss ratio) averaged across these pairs is significantly lower than chance ($M = 0.43$, $SD = 0.12$, $t(19) = 2.44$, $p < 0.05$). Thus, in support of H1B, when two gambles are ranked differently based on expected value and gain-loss ratio, people favor the gamble with lower expected monetary value.

2.2.2. Risk Preferences (H2). To assess risk preferences, we analyzed choice shares when gambles have the same expected value. This is the case for 80 of the 260 gamble pairs (see category 3). When gambles have positive expected value (40 gamble pairs), the likelihood of choosing the less risky gamble (the gamble with lower outcome variance) is significantly higher than chance ($M = 0.79$, $SD = 0.10$, $t(39) = 17.56$, $p < 0.001$). When gambles have negative expected value (40 gamble pairs), the likelihood of choosing the more risky gamble (the gamble with higher outcome variance) is significantly higher than chance ($M = 0.66$, $SD = 0.17$, $t(39) = 5.64$, $p < 0.001$).

To examine sensitivity to gains and losses more generally, we computed the difference between gains ($\Delta g = g_L - g_R$) and the difference between losses for each gamble pair ($\Delta l = (-l_L) - (-l_R)$). We then regressed the choice shares for gamble L on Δg, Δl, a dummy variable indicating whether the expected value of the gambles was positive (0) versus negative (1), the interaction between the dummy variable and Δl, and the interaction between the dummy variable and Δg. The interaction between the dummy variable and Δl ($t(254) = 5.05$, $p < 0.001$) as well as the interaction between the dummy variable and Δg were significant ($t(254) = 6.46$, $p < 0.001$). When expected value was positive, choice was affected more by variation in losses ($B = -0.04$, $SE = 0.002$, 95% CI: $[-0.045, -0.038]$, $t(127) = -23.19$, $p < 0.001$) than by variation in gains ($B = 0.02$, $SE = 0.002$, 95% CI: $[0.018, 0.025]$, $t(127) = 12.25$, $p < 0.001$). When expected value was negative, choice was affected more by variation in gains ($B = 0.04$, $SE = 0.002$, 95% CI: $[0.034, 0.041]$, $t(127) = 21.36$, $p < 0.001$) than by variation in losses ($B = -0.03$, $SE = 0.002$, 95% CI: $[-0.031, -0.023]$, $t(127) = -16.02$, $p < 0.001$). Note that the absolute values of the 95% confidence intervals for gains and losses are nonoverlapping when expected value is positive as well as when expected value is negative. This indicates that losses are weighted significantly more than gains when expected value is positive and gains are weighted significantly more than losses when expected value is negative.

In sum, our analyses support H2A and H2B. We find that differences in the loss portions of gambles are more influential than equal differences in the gain portions when expected value is positive and that differences in the gain portions of gambles are instead more influential than equal differences in the loss potions when expected value is negative. As a consequence, people are risk averse when choosing between gambles with positive expected value but risk seeking when choosing between gambles with negative expected value.

2.2.3. Preference Extremity (H3–H7). *Preference Extremity When Gain-Loss Ratio Is Diagnostic vs. Not Diagnostic* (H3). To examine preference extremity as a function of whether gain-loss ratio is diagnostic or not, we compared the extremity in choice shares (the absolute difference from indifference or 50%) for the 240 gamble pairs where gain-loss ratio favors one of the gambles with the 20 gamble pairs where gain-loss ratio is not diagnostic (see category 4). In line with H3, choice shares are more extreme when gain-loss ratio is diagnostic ($M = 0.33$, $SD = 0.16$) than when gain-loss ratio is not diagnostic ($M = 0.17$, $SD = 0.10$, $t(258) = 4.31$, $p < 0.001$). This result cannot be accounted for by differences in expected value between the two gambles in a pair because this difference does not vary depending on whether gain-loss ratio is diagnostic or not ($t(258) = -0.43$, $p = 0.67$). Another alternative explanation could be that the gamble pairs for which gain-loss ratio is not diagnostic also differ less in terms of risk. To rule out the possibility that differences in risk instead of gain-loss ratio explain the result above, we computed the difference in outcome variance between the two gambles in each pair. In contrast to this alternative account, the difference in terms of risk is directionally higher when gain-loss ratio is not diagnostic ($M = 334$, $SD = 115$) than when gain-loss ratio is diagnostic ($M = 273$, $SD = 181$, $t(258) = 1.49$, $p = 0.14$). It is interesting to note that, even though choice shares are more extreme when gain-loss ratio is diagnostic than when it is not, people are not indifferent when gain-loss ratio is not diagnostic ($t(19) = 7.81$, $p < 0.001$). This implies that gain-loss ratio cannot be the only decision strategy used by our participants, in line with the idea that people can adaptively shift between decision rules (Payne 1982).

Preference Extremity When Expected Value Is Positive vs. Negative (H4 *and* H5). The difference between two gambles in terms of gain-loss ratio is larger for gambles with positive expected value than for equivalent gambles with inverted gain and loss portions and thus negative expected value (see §1.3). In the current study, the mean absolute difference between gambles in terms of gain-loss ratio is 1.59 ($SD = 1.35$) in the positive and 0.28 ($SD = 0.17$) in the negative expected value condition ($t(238) = 10.54$, $p < 0.001$). To test whether preference extremity varies as a function of expected value domain, we regressed the extremity of choice shares for the 240 gamble pairs where gain-loss ratio is diagnostic on a dummy variable indicating whether expected value is positive (0) or negative (1). In line with H4, choice shares are more extreme when gambles have positive ($M = 0.35$, $SD = 0.14$) than when gambles have negative expected value ($M = 0.30$, $SD = 0.17$, $B = -0.05$, $SE = 0.02$, $t(238) = -2.45$, $p < 0.05$). To examine whether absolute differences in gain-loss ratio mediate the effect of expected value domain on choice share extremity (H5), we calculated the absolute difference in gain-loss ratio between gambles for each of the 240 gamble pairs and then regressed choice share extremity on expected value domain and the absolute difference between the two gambles' gain-loss ratios. Absolute differences in gain-loss ratio are positively related to choice share extremity ($B = 0.06$, $SE = 0.01$, $t(237) = 6.79$, $p < 0.001$) and the residual effect of expected value domain is not significant after controlling for absolute differences in gain-loss ratio ($B = 0.04$, $SE = 0.02$, $t(237) = 1.62$, $p = 0.11$). We examined the significance of this mediation with a bootstrap analysis (Preacher and Hayes 2004) and find that the 95% confidence interval for the indirect effect does not include 0 (95% CI: $[-0.10, -0.07]$).

Decision Time When Expected Value Is Positive vs. Negative (H6 *and* H7). To test whether decision time varies as a function of expected value domain, we regressed decision time for the 240 gamble pairs where gain-loss ratio is diagnostic on a dummy variable indicating whether expected value is positive (0) or negative (1). Following standard practice, we log-transformed the raw response times (adding a constant of 1 to avoid negative values) to reduce the impact of outliers. In line with H6, participants take longer to decide when gambles have negative ($M = 1.73$, $SD = 0.17$) than when gambles have positive expected values ($M = 1.58$, $SD = 0.19$, $B = 0.15$, $SE = 0.02$, $t(238) = 6.28$, $p < 0.001$). To examine whether absolute differences in gain-loss ratio mediate the effect of expected value domain on decision time (H7), we regressed decision time on expected value domain and the absolute difference between the two gambles' gain-loss ratio. Absolute differences in gain-loss ratio are negatively related to decision time ($B = -0.07$, $SE = 0.01$, $t(237) = 6.16$, $p < 0.001$) and the residual effect of expected value domain is much smaller after controlling for absolute differences in gain-loss ratio ($B = 0.06$, $SE = 0.03$, $t(237) = 2.10$, $p < 0.05$). We examined the significance of this mediation with a bootstrap analysis (Preacher and Hayes 2004) and find that the 95% confidence interval for the indirect effect does not include 0 (95% CI: $[0.06, 0.13]$).

In sum, the data provide strong evidence that participants' behavior was affected by the discriminability of gain-loss ratio. Preferences are more extreme when gain-loss ratio is diagnostic than when it is not (H3) and are more extreme when expected value is positive than when it is negative (H4). The latter effect is mediated by actual differences between the gambles' gain-loss ratios (H5). Moreover, reflecting greater deliberation and decision difficulty, decision time is longer in the negative than in the positive expected value domain (H6) and this effect is again mediated by differences between the gambles' gain-loss ratios (H7).

2.3. Alternative Accounts

Prospect Theory. Although most hypotheses above uniquely follow from sensitivity to gain-loss ratio, we used a stochastic choice analysis to formally compare the ability of prospect theory with the ability of gain-loss ratio to account for the choice shares (Wu and Gonzalez 1996, Wu and Markle 2008). Let the probability of choosing gamble L over gamble R be determined by a logistic model: $P(L > R) = 1/[1 + \exp(-\mu[U(L) - U(R)])]$. We first estimated this model assuming that the utility of gambles is determined by prospect theory ($U(L) = pg_L^{\alpha} - \lambda(1-p)(-l_L)^{\beta}$ and $U(R) = pg_R^{\alpha} - \lambda(1-p)(-l_R)^{\beta}$) with standard parameter values; following Tversky and Kahneman (1992), we set α and β to 0.88 and λ to 2.25. We then estimated the model assuming that the utility of gambles is determined by gain-loss ratio ($U(L) = (pg_L)/[(1-p)(-l_L)]$ and $U(R) = (pg_R)/[(1-p)(-l_R)]$). We fitted these models using nonlinear regression where the likelihood of the choice shares is maximized over the 260 gamble pairs in Table 2. Both models have one free parameter, μ, capturing the sensitivity of choice shares to differences in utility and reflecting the randomness in the choice process. Thus, the predictive validity of the models can be directly compared. The correlation between actual and predicted choice shares was lower and the mean absolute distance between actual and predicted choice shares was higher when utility follows prospect theory with standard parameter values ($R = 0.72$, $MAD = 0.20$, $\mu = 0.22$, $t(259) = 6.38$, $p < 0.001$) than when utility follows gain-loss ratio ($R = 0.90$, $MAD = 0.12$, $\mu = 4.56$).

Other research has found lower values for α and β indicating greater curvature in the value function (Wu and Gonzalez 1996). We therefore reestimated the model with the parameter values found by Wu and Gonzalez: $\alpha = \beta = 0.5$. We again set λ to 2.25. These parameter values fit the data better ($R = 0.78$,

$MAD = 0.18$, $\mu = 1.18$) but still substantially worse than when utilities follow gain-loss ratio ($t(259) = 5.28$, $p < 0.001$). Other research has instead doubted the existence of loss aversion when people choose between mixed gambles (for a review, see Yechiam and Hochman 2013). We therefore reestimated the model with λ set to 1. We again set α and β to 0.88. Model fit improves with these parameter values ($R = 0.85$, $MAD = 0.14$, $\mu = 0.71$) but is still lower than when utilities follow gain-loss ratio ($t(259) = 2.60$, $p = 0.01$).

The analyses above suggest that prospect theory fits the data better as parameter values become less consistent with the psychological underpinnings of the theory. For example, setting λ to 1 implies removing the key assumption of prospect theory that people are loss averse. As a next step we estimate the model with three free parameters: $\alpha = \beta$, λ, and μ. To test for robustness we repeated the estimation procedure using different starting values. The model always converged on the same parameter values: $\alpha = \beta = 0.32$ (95% CI: $[0.27, 0.37]$), $\lambda = 1.14$ (95% CI: $[1.10, 1.17]$), and $\mu = 10.76$ (95% CI: $[7.80, 13.73]$).[3] Not surprisingly, this model fits the data very well ($R = 0.95$, $MAD = 0.08$), better than when utilities are determined by gain-loss ratio ($t(259) = -7.78$, $p < 0.001$). However, the best-fitting parameter values are in line with the results of our simulation (see §1.4 and Appendix C). We find strong curvature in the value function and a loss-aversion parameter that lies close to 1. Our estimate for λ is significantly higher than 1 but this is expected also based on a stochastic decision rule that is sensitive to gain-loss ratio. A loss-aversion parameter that lies so close to 1 may seem surprising in light of many studies that have documented strong asymmetries in people's subjective responses to gains and losses (for reviews, see Baumeister et al. 2001, Rozin and Royzman 2001). However, it is consistent with a more recent stream of research that casts doubt on the universality of loss aversion (Battalio et al. 1990, Erev et al. 2008, Ert and Erev 2008, Kermer et al. 2006, Nilsson et al. 2011). Many of these studies were carried out using mixed gambles and Yechiam and Hochman (2013) propose that the literature is divided because some studies use single-domain gambles whereas other studies use mixed gambles.

In sum, prospect theory with standard parameter values cannot account for the data as well as sensitivity to gain-loss ratio. When all parameters are estimated freely, prospect theory fits the data very well but the best-fitting parameter values suggest that sensitivity to gain-loss ratio may be the real driver of choice between mixed gambles. This conclusion is corroborated by the previous analyses, such as the finding of more sensitivity to gains when expected value is negative.

Logarithmic Specification of Prospect Theory's Value Function with No Loss Aversion. A simple additive model with a logarithmic value function over gains and losses makes the same ordinal predictions as gain-loss ratio (if $GLR_L > GLR_R \Rightarrow \log(GLR_L) > \log(GLR_R) \Rightarrow \log(g_L) - \log(-l_L) > \log(g_R) - \log(-l_R)$). In other words, if people transform gains and losses according to a logarithmic value function and then combine subjective gains and losses according to an additive integration rule, the ranking of mixed gambles would be identical to their ranking according to gain-loss ratio. Note that this model is equivalent to prospect theory with a logarithmic specification for the value function and no loss aversion. However, according to this model people should discriminate equally between gambles in the negative expected value domain and the same gambles with inverted gain and loss portions in the positive expected value domain. This is because the effect of adding a constant to the gain and loss portions of a gamble on the difference between log-transformed gains and losses does not depend on whether the expected value of the gambles is positive or negative (e.g., $[\ln(20) - \ln(10)] - [\ln(40) - \ln(20)] = -0.69$ and $[\ln(10) - \ln(20)] - [\ln(20) - \ln(40)] = 0.69$). In other words, an additive model with a logarithmic value function does not predict H4–H7.

Alternative-Based vs. Attribute-Based Ratio Comparison. It is possible that people compare attribute-based ratios instead of alternative-based ratios. That is, people may compare the ratio of the gains with the ratio of the losses instead of the gain-loss ratio of the first gamble with the gain-loss ratio of the second gamble. Accordingly, when choosing between gambles L and R, people may select gamble L if $g_L/g_R > l_L/l_R$, and gamble R otherwise. That is, people may prefer a gamble if the proportional increase in the gain outweighs the proportional increase in the loss. A comparison of attribute-based ratios makes the same ordinal predictions as gain-loss ratio and thus makes the same predictions with regard to

[3] Note that high values for μ indicate extreme sensitivity to small differences in utilities. This raises questions about the estimated value of α because a very large sensitivity parameter allows the very small differences in utilities resulting from small αs to produce meaningful differences in choice predictions. To assess the model's ability to accurately estimate the values for α and β when μ is allowed to freely vary, we performed two additional analyses. First, we reestimated the best-fitting parameter values constraining μ to the $[0.1, 5]$ range. The estimated value of α is comparable to the one reported above ($\alpha = 0.45$). Unsurprisingly, the estimated value of μ in this model is 5. Second, we generated data using a range of prospect theory parameter values and then estimated the stochastic model on these simulated data. In all cases, the model was able to correctly recover the α, λ, and μ parameters used to generate the data.

suboptimal monetary outcomes (H1), risk preferences (H2), and preference extremity depending on whether gain-loss ratio is diagnostic or not (H3). However, people deciding purely based on attribute-based ratios should discriminate equally between gambles in the negative expected value domain and the same gambles with inverted gain and loss portions in the positive expected value domain. Compare for instance gambles L $(25, 0.5; -10)$ and R $(15, 0.5; -5)$ with gambles L' $(10, 0.5; -25)$ and R' $(5, 0.5; -15)$ with inverted gain and loss portions. The absolute difference between the gambles in terms of gain-loss ratio is higher when expected value is positive $(|12.5/5 - 7.5/2.5| = |2.5 - 3| = 0.5)$ than when expected value is negative $(|5/12.5 - 2.5/7.5| = |0.4 - 0.33| = 0.07)$. Instead, the absolute difference between the gain-gain ratio and the loss-loss ratio is the same regardless of whether expected value is positive $(|12.5/7.5 - 5/2.5| = |1.67 - 2| = 0.33)$ or negative $(|5/2.5 - 12.5/7.5| = |2 - 1.67| = 0.33)$. In other words, sensitivity to attribute-based ratios does not predict H4–H7.

2.4. Summary

Sensitivity to gain-loss ratio provides a compelling and parsimonious account for the choice data of Study 1. Participants show a strong tendency to maximize gain-loss ratio, even when doing so implies lower monetary outcomes (H1). They are risk averse when the expected value of gambles is positive (H2A) but risk seeking when the expected value of gambles is negative (H2B). Choice shares are more extreme when gain-loss ratio is diagnostic (H3) and more extreme when expected value is positive than when it is negative (H4). The latter effect is mediated by differences in gain-loss ratio (H5). Participants take less time to choose when expected value is positive than when it is negative (H6) and this effect is mediated by differences in gain-loss ratio (H7). This is consistent with the idea that gambles are easier to discriminate when expected value is positive (and gain-loss ratio ranges between 1 and $+\infty$) than when expected value is negative (and gain-loss ratio ranges between 0 and 1). Finally, estimating prospect theory yields extreme curvature in the value function and little loss aversion, consistent with the pattern expected if choice is stochastic and driven by gain-loss ratio (see §1.4 and Appendix C). Prospect theory (or other specifications assuming additive utility) is thus an unlikely account for our findings. The results are also less consistent with an account based on sensitivity to attribute-based ratios according to which people compare ratios of gains with ratios of losses.

3. Study 2

Study 2 adds to the previous study in two ways. First, Study 1 examined choice between mixed gambles but, at times, people need to assess the attractiveness of a single gamble presented in isolation. Study 2 therefore generalizes the results of the previous studies from a joint- to a single-evaluation context. Early research in judgment and decision making shows that payoffs tend to have a weaker influence on judgments of attractiveness than on choice (Slovic and Lichtenstein 1968, Goldstein and Einhorn 1987). Bateman et al. (2007) offered a dramatic demonstration of this insensitivity. They showed that people rate the attractiveness of the possibility of winning \$3 about the same as the attractiveness of the possibility of winning \$12. They replicated this finding for various probabilities and for outcomes ranging from \$3 to \$120. The difference between joint and separate evaluations and the more general issue of scope sensitivity in judgments has attracted much attention in the judgment and decision-making literature (Hsee et al. 1999, 2005; Hsee and Zhang 2010). Many dimensions are inevaluable when stimuli are presented in isolation. In Study 2, we examine the evaluability of gain-loss ratio. Specifically, we ask participants to rate the attractiveness of one mixed gamble and orthogonally manipulate gain-loss ratio (i.e., the proportional difference between gain and loss) and expected value (i.e., the absolute difference between gain and loss) between participants.

Second, Study 2 examines our assumption that the integration rule used to combine payoffs varies depending on whether the decision involves mixed gambles versus single-domain gambles. We argue that when evaluating mixed gambles, people care about efficiency or the rate of exchange between resources gained and resources lost. The notion of efficiency loses meaning in the case of single-domain gambles—because in this context there is no exchange of positives for negatives. Only gambles involving gains and losses should thus probe concerns about the ratio between the possible payoffs. Accordingly, people should favor mixed gambles with larger payoff ratios (i.e., gain-loss ratios) but they should not favor single-domain gambles with larger payoff ratios (i.e., gain-gain or loss-loss ratios).

3.1. Method

We presented 512 respondents from Amazon Mechanical Turk with one of 16 gambles (193 females, $M_{age} = 29.97$, $SD = 9.17$). Participants rated the gamble on a scale from 0 (*neutral*) to 10 (*extremely attractive*). There were eight mixed gambles: $A(6, 0.5; -2)$, $B(8, 0.5; -4)$, $C(9, 0.5; -3)$, $D(12, 0.5; -6)$, $E(60, 0.5; -20)$, $F(80, 0.5; -40)$, $G(90, 0.5; -30)$, $H(120, 0.5; -60)$. We designed these mixed gambles such that the ratio of gains over losses ($GLR_B = GLR_D = GLR_F = GLR_H = 2 < GLR_A = GLR_C = GLR_E = GLR_G = 3$) varied independently from the absolute difference between gains and losses, or expected value ($EV_A = EV_B = 2 < EV_C = EV_D = 3 < EV_E = EV_F = 20 < EV_G = EV_H = 30$). We converted the loss of the mixed gambles into another gain to create the eight single-domain gambles: $A'(6, 0.5; 2)$, $B'(8, 0.5; 4)$, $C'(9, 0.5; 3)$, $D'(12, 0.5; 6)$, $E'(60, 0.5; 20)$, $F'(80, 0.5; 40)$, $G'(90, 0.5; 30)$, $H'(120, 0.5; 60)$. The ranking of these gambles in terms of expected value ($EV_{A'} = 4 < EV_{B'} = EV_{C'} = 6 < EV_{D'} = 9 < EV_{E'} = 40 < EV_{F'} = EV_{G'} = 60 < EV_{H'} = 90$) differed from their ranking based on the ratio of the larger gain over the smaller gain ($GGR_{B'} = GGR_{D'} = GGR_{F'} = GGR_{H'} = 2 < GGR_{A'} = GGR_{C'} = GGR_{E'} = GGR_{G'} = 3$). Note that the difference between the single-domain gambles in terms of gain-gain ratio is equal to the difference between the mixed gambles in terms of gain-loss ratio ($\Delta GGR' = \Delta GLR = 1$).

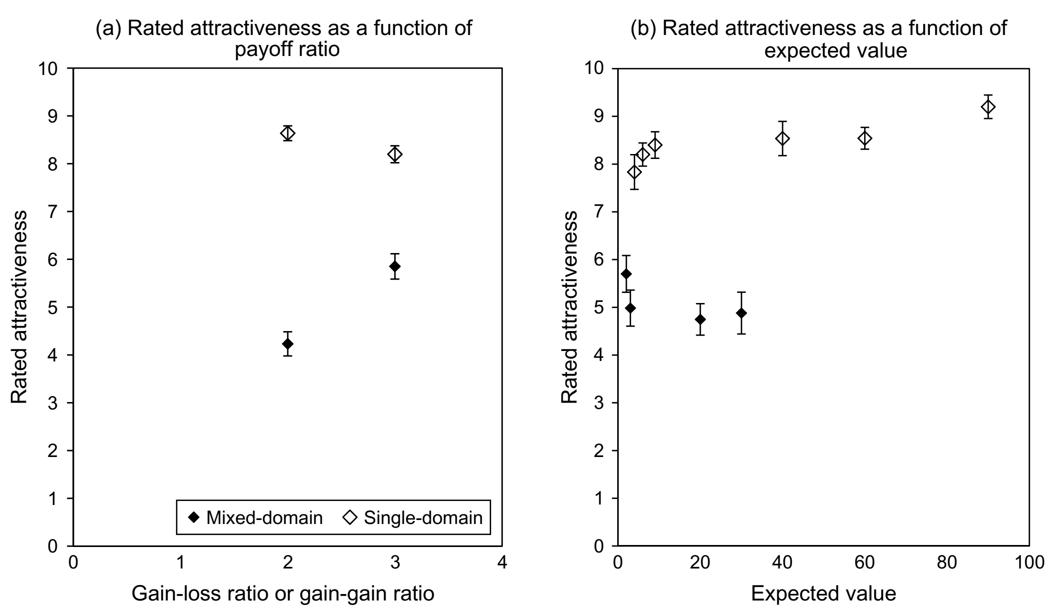
3.2. Results

Figure 2 indicates the mean rated attractiveness for single-domain gambles (white diamonds) and mixed gambles (black diamonds) as a function of payoff ratio (panel (a)) and expected value (panel (b)). Attractiveness ratings appear to be a function of payoff ratio for mixed gambles but not for single-domain gambles. We examine the statistical significance of this pattern below.

3.2.1. Risk Preferences for Mixed Gambles (H2A). We examined whether gain-loss ratio influences judgments of attractiveness for mixed gambles presented in isolation. At each level of expected value (2 versus 3 versus 20 versus 30), there are two gambles that differ in terms of the magnitude of their outcomes. The gamble with the larger outcomes is obtained by adding a constant to the gain and loss portions of the gamble with the smaller outcomes. For instance, gamble $B(8, 0.5; -4)$ can be obtained by adding a constant of 2 to the gain and loss portions of gamble $A(6, 0.5; -2)$. When expected value is equal across gambles and positive, gambles with smaller outcomes (here, the less risky gambles A, C, E, and G) have higher gain-loss ratios than gambles with larger outcomes (here, the more risky gambles B, D, F, and H; see §1.2). In line with sensitivity to gain-loss ratio, we find that participants rate gambles with smaller outcomes as more attractive than gambles with larger outcomes ($ACEG$ versus $BDFH$: 5.85 versus 4.23, $t(247) = 4.41$, $p < 0.001$). This result supports our contention that people are more sensitive to variation in losses than to equal variation in gains, and thus risk averse, when expected value is positive (H2A).

3.2.2. Single-Domain Gambles. To examine whether the use of a multiplicative integration rule generalizes to single-domain gambles that only involve positive outcomes, we regressed attractiveness ratings on gain-gain ratio and expected value. Although gambles with higher expected value were rated as more attractive than gambles with lower expected value ($B = 0.01$, $SE = 0.004$, $t(246) = 2.25$, $p < 0.05$), gambles with higher gain-gain ratios were rated the same as gambles with lower gain-gain ratios ($B = -0.28$, $SE = 0.24$, $t(260) = -1.17$, $p > 0.24$). This result is

Figure 2 Results of Study 2



Notes. In panel (a) the relationship is positive and significant for mixed gambles but not significant for single-domain gambles. In panel (b) the relationship is positive and significant for single-domain gambles but not significant for mixed gambles.

inconsistent with the use of a multiplicative integration rule. Although beyond the scope of this paper, the observed sensitivity to expected value for single-domain gambles is interesting. Bateman et al. (2007) found that multiplying the expected value of a single-domain gamble by approximately a factor of 10 did not result in a positive change in the gamble's attractiveness. There are several differences between the stimuli used in the two studies that might explain this discrepancy (e.g., related to probabilities or to the difference between the magnitudes of the two payoffs). Additional research should explore the process used by people to judge the attractiveness of single-domain gambles presented in isolation.

4. Study 3

Study 2 shows that people are sensitive to differences in gain-loss ratio when evaluating mixed gambles presented in isolation, with larger gain-loss ratios resulting in higher ratings of attractiveness. In contrast, attractiveness ratings for single-domain gambles were unrelated to gain-gain ratio. The attractiveness of single-domain gambles was instead significantly predicted by differences in expected value. Study 3 further explores the influence of gain-loss ratio on the evaluation of mixed gambles presented in isolation. Whereas Study 2 only used gambles with positive expected values, Study 3 uses gambles with positive as well as negative expected values. In addition to H2A, this design allows testing the prediction of risk seeking for gambles with negative expected value (H2B) and the prediction of greater preference extremity for gambles with positive expected value (H4).

4.1. Method

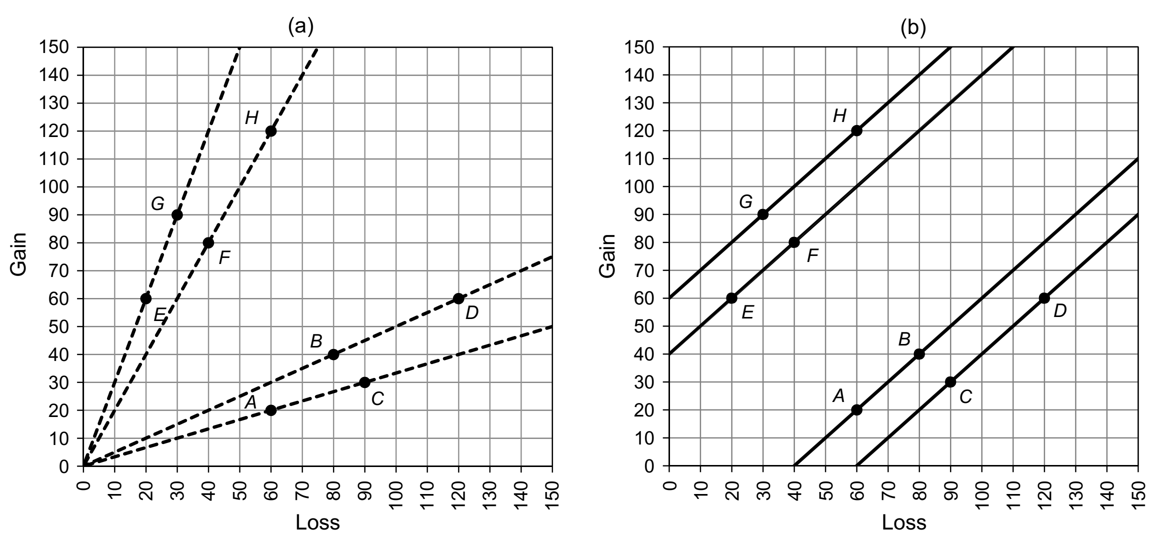
We presented 254 business undergraduates at a European university with one of eight gambles offering equal probability of winning and losing (118 females, $M_{\text{age}} = 21.19$, $SD = 2.83$). Participants rated the gamble on a scale from -10 (*extremely unattractive*) to $+10$ (*extremely attractive*). The eight gambles were $A(20, 0.5; -60)$, $B(40, 0.5; -80)$, $C(30, 0.5; -90)$, $D(60, 0.5; -120)$, $E(60, 0.5; -20)$, $F(80, 0.5; -40)$, $G(90, 0.5; -30)$, and $H(120, 0.5; -60)$. We designed these gambles such that the ratio of gains over losses ($GLR_A = GLR_C = 0.33 < GLR_B = GLR_D = 0.5 < GLR_F = GLR_H = 2 < GLR_E = GLR_G = 3$; see Figure 3(a)) varied independently from the absolute difference between objective gains and losses, or expected value ($EV_C = EV_D = -30 < EV_A = EV_B = -20 < EV_E = EV_F = 20 < EV_G = EV_H = 30$; see Figure 3(b)). Note that the last four gambles are identical to the first four gambles except for the fact that the gain and loss portions are inverted, reversing the sign of their expected value.

4.2. Results

Figure 4 plots attractiveness ratings as a function of gain-loss ratio (panel (a)) and expected value (panel (b)). Attractiveness ratings appear to be a function of gain-loss ratio. We examine the statistical significance of this pattern below.

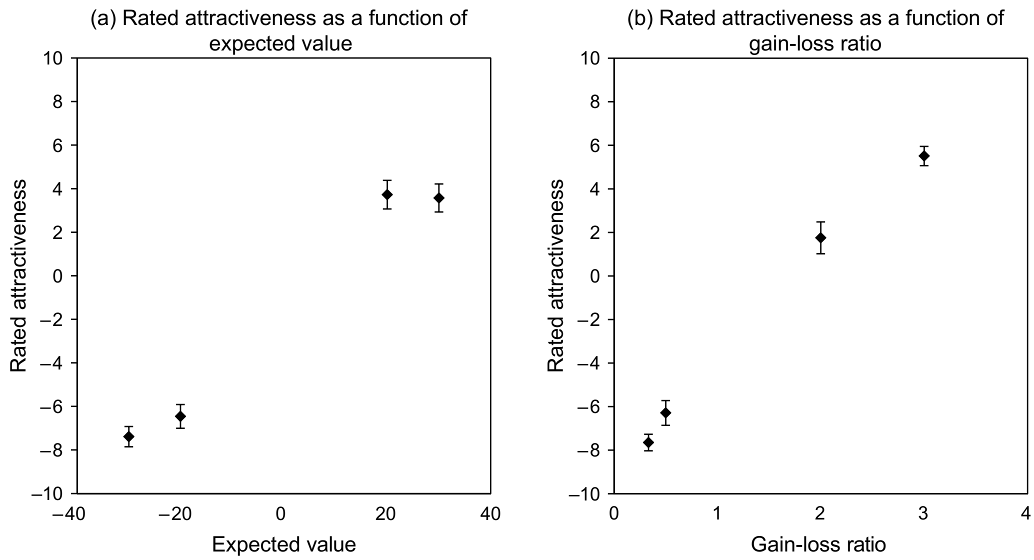
4.2.1. Risk Preferences (H2). At each level of positive expected value (20 versus 30), there are two gambles that differ in terms of the magnitude of their outcomes. The gamble with the larger outcomes is obtained by adding a constant to the gain and loss portions of the gamble with the smaller outcomes. When expected value is equal across gambles and

Figure 3 Design of Study 3



Notes. (a) Dashed lines connect gambles that are equal in terms of gain-loss ratio; gambles to the left of the line have a higher gain-loss ratio, and gambles to the right of the line have a lower gain-loss ratio. (b) Solid lines connect gambles that are equal in terms of expected value; gambles to the left of the line have a higher expected value, and gambles to the right of the line have a lower expected value.

Figure 4 **Results of Study 3**



positive, gambles with smaller outcomes (here, the less risky gambles *E* and *G*) have higher gain-loss ratios than gambles with larger outcomes (here, the more risky gambles *F* and *H*; see §1.2). In line with sensitivity to gain-loss ratio, we find that participants rate gambles with smaller outcomes as more attractive than gambles with larger outcomes (*EG* versus *FH*: 5.50 versus 1.75, $t(119) = 4.42$, $p < 0.001$). This result supports our contention that people are more sensitive to variation in losses than to equal variation in gains, and thus risk averse, when expected value is positive (H2A).

Similarly, at each level of negative expected value (−20 versus −30), there are two gambles that differ in terms of the magnitude of their outcomes. The gamble with the larger outcomes is obtained by adding a constant to the gain and loss portions of the gamble with the smaller outcomes. When expected value is equal across gambles and negative, gambles with larger outcomes (here, the more risky gambles *B* and *D*) have higher gain-loss ratios than gambles with smaller outcomes (here, the less risky gambles *A* and *C*; see §1.2). In line with sensitivity to gain-loss ratio, we find that participants rate gambles with larger outcomes as more attractive than gambles with smaller outcomes (*BD* versus *AC*: −6.28 versus −7.65, $t(131) = 1.85$, $p = 0.07$). Although the two-tailed test is marginally significant, these means are in line with our contention that people are more sensitive to variation in gains than to equal variation in losses, and thus risk seeking, when expected value is negative (H2B).

4.2.2. Preference Extremity (H4). Recall that gambles *A*, *B*, *C*, and *D* are identical to gambles *E*, *F*, *G*, and *H* except for inverted gain and loss portions. When gambles have negative expected value the difference between gambles in terms of gain-loss ratio is smaller than when gambles have positive expected value (see §1.3). To test whether preferences are less extreme when expected value is negative (H4), we compared the difference in rated attractiveness between gambles with low and high gain-loss ratios in the negative expected value domain (*AC* versus *BD*) with the difference in rated attractiveness between gambles with low and high gain-loss ratios in the positive expected value domain (*FH* versus *EG*). These differences were significantly different from each other ((*AC*–*BD*) versus (*FH*–*EG*): 1.37 versus 3.75, $t(250) = 2.14$, $p < 0.05$). The asymmetry in the rated attractiveness of gambles with gain-loss ratios smaller versus larger than 1 is in line with the asymmetries we found in Study 1 for choice shares and decision times, a pattern of results that is uniquely predicted by sensitivity to gain-loss ratio.

5. Study 4: Reanalysis of Keysar et al. (2012, Study 2)

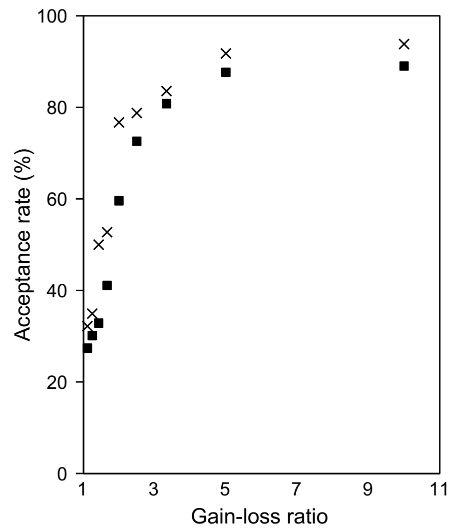
Study 3 replicates the results of Study 2 for mixed gambles with positive expected value and generalizes the findings of Study 2 to mixed gambles with negative expected value. Study 3 also replicates the results of Study 1 concerning the effect of differences in preference extremity for gambles in the positive and negative expected value domain. In line with H4, participants were more sensitive to differences between gambles when expected value was positive than when the gambles' gains and losses were reversed and hence expected value was negative.

In Study 1, we asked participants to choose between two mixed gambles. This task mimics many situations in which people have to select the best course

Table 3 Design and Results of Study 4

Gamble	Gain	Loss	*EV*	*GLR*	Acceptance rate (%)
A	2,000	200	900	10	94
B	3,000	600	1,200	5	92
C	4,000	1,200	1,400	3.33	84
D	5,000	2,000	1,500	2.5	79
E	6,000	3,000	1,500	2	77
F	7,000	4,200	1,400	1.67	53
G	8,000	5,600	1,200	1.43	50
H	9,000	7,200	900	1.25	35
I	10,000	9,000	500	1.11	32
J	110,000	11,000	49,500	10	89
K	120,000	24,000	48,000	5	88
L	130,000	39,000	45,500	3.33	81
M	140,000	56,000	42,000	2.5	73
N	150,000	75,000	37,500	2	60
O	160,000	96,000	32,000	1.67	41
P	170,000	119,000	25,500	1.43	33
Q	180,000	144,000	18,000	1.25	30
R	190,000	171,000	9,500	1.11	27

Figure 5 Results of Study 4



Notes. Acceptance rate as a function of gain-loss ratio. Correspondence between acceptance rate and gain-loss ratio is perfect for gambles with high stakes (squares) and low stakes (crosses).

of action between two or more options that differ in terms of positive and negative outcomes. In other situations people are instead faced with one possible course of action and they have to decide whether to stick to the status quo or deviate from it. These situations map onto the decision to accept or reject a mixed gamble. To generalize the findings to a different context and to different gambles, we examine acceptance rates for gambles that are presented one at the time. We do so by relying on recently published data by Keysar et al. (2012, Study 2).

5.1. Method

To examine the effect of language (native versus second) on risky decision making, Keysar and colleagues asked 146 Korean participants to accept or reject 18 mixed gambles with positive expected value, half of these having high stakes and the other half low stakes. The study was administered either in English or Korean (see Keysar et al. 2012 for additional information about the study setting and procedures). We present all gambles in Table 3 together with the observed acceptance rates.

5.2. Results

Figure 5 plots acceptance rates as a function of gain-loss ratio. Squares indicate gambles with high stakes and crosses indicate gambles with low stakes. Regardless of whether stakes are high or low, acceptance rates increase linearly as gain-loss ratio increases from one to three and then level off close to 100% (the highest possible acceptance rate).

5.2.1. Expected Monetary Value (H1). To analyze this data in a similar way as Study 1, we first created a data set with all pairwise combinations of gambles. This yields a data set of 153 gambles pairs $((18 \times 17)/2)$. We can now compare the acceptance rates for each of the 18 gambles with the acceptance rates for the other 17 gambles in the study. To test H1, we used the 140 gamble pairs for which gain-loss ratio and expected value either favored the same option or favored different options (i.e., we excluded gamble pairs for which expected value is equal and gamble pairs for which gain-loss ratio is equal). When gain-loss ratio favored the same gamble as expected value, the acceptance rate for the gamble with the higher expected value was higher than the acceptance rate for the gamble with the lower expected value for 95% of gamble pairs (87 out of 92). In other words, consistent with H1A participants almost always accepted the gamble with more favorable expected monetary outcomes more often than the gamble with less favorable expected monetary outcomes. Instead, when gain-loss ratio and expected value were dissociated, there was no gamble pair for which the acceptance rate for the gamble with the higher expected value was higher than the acceptance rate for the gamble with the lower expected value (0 out of 48). In other words, consistent with H1B, participants always accepted the gamble with less favorable expected monetary outcomes (but a higher gain-loss ratio) more often than the gamble with more favorable expected monetary outcomes. This difference is statistically significant ($\chi^2(1) = 119.90$, $p < 0.001$).

5.2.2. Risk Preferences (H2A). To test H2A, we first used the four gamble pairs for which gambles had equal expected value. For these gamble pairs, participants always accepted the gamble with lower outcome variance more often than the gamble with higher outcome variance. In other words, participants were risk averse. To examine sensitivity to gains and losses more generally, we computed the difference between gains ($\Delta g = g_L - g_R$) and the difference between losses for each gamble pair ($\Delta l = (-l_L) - (-l_R)$). We then regressed the difference in acceptance rates between the gambles on Δg and Δl. This analysis is similar to our analysis in Study 1 and allows us to use all 153 gamble pairs. The absolute values for the 95% confidence intervals for the effect of Δg (95% CI: [0.0000028, 0.0000042]) and Δl (95% CI: [−0.0000064, −0.0000045]) were nonoverlapping. In other words, the difference in acceptance rates was affected more by variation in losses than by variation in gains.

5.2.3. Preference Extremity (H3). To test H3, we analyzed the absolute difference in acceptance rates as a function of whether gain-loss ratio is diagnostic or not. Acceptance rates were closer for the eight gamble pairs where gain-loss ratio is not diagnostic ($M = 0.08$, $SD = 0.06$) than for the 144 gamble pairs where gain-loss ratio is diagnostic ($M = 0.30$, $SD = 0.20$, $t(151) = 3.29$, $p < 0.01$). In other words, preferences are less extreme when gain-loss ratio is not diagnostic.

5.2.4. Additional Analysis. To assess whether prospect theory can provide an alternative account for the data, we conducted two analyses. First, we predicted acceptance rates using the best-fitting parameter values for α, β, and λ from Study 1 ($\alpha = \beta = 0.33$, $\lambda = 1.14$). The correlation between acceptance rates and the values of gambles according to prospect theory computed separately for gambles with high stakes and gambles with low stakes is perfect for both types of gambles (Spearman's $\rho = 1$). Also the correlation computed across high and low stakes is very high (Spearman's $\rho = 0.86$, $p < 0.001$). We then compared this correlation with the one for gain-loss ratio (Spearman's $\rho = 0.97$, $p < 0.001$) following the approach of Meng et al. (1992). The 95% confidence interval for the difference between both Fisher z-transformed correlation coefficients excludes zero (95% CI: [0.42, 1.33]) indicating that prospect theory with parameter values from Study 1 provides a worse account for the data than gain-loss ratio.

Second, we estimated parameter values using the current data. We modeled the acceptance rate for each gamble with a logistic function:

$$\textit{Acceptance rate} = 1/(1 + \exp[-U(L)]),$$

where $U(L)$ is determined according to the same formula used in the simulation study and in Study 1. The mean squared difference between observed and predicted acceptance rates is lowest when $\alpha = 0.27$ and $\lambda = 1.14$. These parameter values are almost identical to those estimated in Study 1.

Given the differences between Studies 1 and 4 in terms of the gambles' payoffs, dependent variables, and participant populations (Western versus East Asian), the high predictive validity of gain-loss ratio in both studies and the consistency of the best-fitting prospect theory parameters is remarkable. In both studies, the best-fitting parameter estimates approach the parameter values that allow prospect theory to mimic gain-loss ratio (see §1.4). Also note that an account based on attribute-based ratios is not applicable to the data of Study 4 because, like in Studies 2 and 3, people only evaluated one gamble at a time.

6. Study 5: Reanalysis of Sussman and Shafir (2012, Study 3a)

The previous studies indicate sensitivity to gain-loss ratio when individuals are asked to choose between two gambles (Study 1), rate the attractiveness of a gamble presented in isolation (Studies 2 and 3), or decide whether to accept or reject a gamble (Study 4). In all studies we used gambles with equal probabilities of winning and losing. The remaining three experiments assess the robustness of this finding in situations where probabilities are different from 0.5. In Study 5 we use recently published data by Sussman and Shafir (2012) to test whether gain-loss ratio affects the evaluation of mixed decision alternatives for which the probabilities of positive and negative outcomes are equal to 1. Outcomes are oftentimes not stochastic and we expect people to rely on gain-loss ratios in those situations as well.

Objectively, people's net worth is determined by additively integrating assets and debts. that is, regardless of a person's current level of assets and debts, an increase in assets offsets an identical increase in debts. For instance, the net worth of person A with \$41 M in assets and \$5 M in debts is equal to the net worth of person B with \$44 M in assets and \$8 M in debts. Similarly, the net worth of person J with \$2 M in assets and \$38 M in debts is equal to the net worth of person K with \$7 M in assets and \$43 M in debts. In a series of studies, Sussman and Shafir (2012) find that this is not how people perceive wealth. The authors find that increases in debts are weighted more than identical increases in assets when a person has positive net worth, and vice versa, increases in assets are weighted more than identical increases in debts when a person has negative net worth. Thus, the perceived wealth of person B is lower than the perceived wealth of person A and the perceived wealth of person K is higher than the perceived wealth of person J. Sensitivity to gain-loss ratio predicts this pattern of results. Specifically, we argued in §1.2 that when expected value is

Table 4 Design and Results of Study 5

Set	Profile	Assets	Debts	*Net wealth*	*ADR*	Average rank
1	A	41	5	36	8.2	3.59
1	B	44	8	36	5.5	4.41
1	C	55	19	36	2.89	5.00
1	D	71	35	36	2.03	5.16
1	E	77	41	36	1.88	6.31
1	F	94	58	36	1.62	6.63
1	G	112	76	36	1.47	6.69
1	H	136	100	36	1.36	7.22
1	I	154	118	36	1.31	7.91
2	J	2	38	−36	0.05	6.44
2	K	7	43	−36	0.16	5.81
2	L	11	47	−36	0.23	5.09
2	M	15	51	−36	0.29	5.22
2	N	20	56	−36	0.36	5.25
2	O	31	67	−36	0.46	5.00
2	P	40	76	−36	0.53	5.06
2	Q	52	88	−36	0.59	4.81
2	R	63	99	−36	0.64	4.75

Note. *ADR* stands for asset-debt ratio.

positive (here, net worth is positive) people should be more sensitive to variation in losses (here, debts) than to equal variation in gains (here, assets). Conversely, when expected value is negative (here, net worth is negative), people should be more sensitive to variation in gains (here, assets) than to equal variation in losses (here, debts).

6.1. Method

Sussman and Shafir (2012, Study 3a) presented 32 respondents with two sets of 10 financial profiles and asked them to rank the profiles in each set from most to least desirable. The profiles in the first set all had a positive net worth of \$36,000 and the profiles in the second set all had a negative net worth of \$36,000. In each set, nine profiles had mixed outcomes. We present these profiles and their average rank in Table 4. (See Sussman and Shafir 2012 for additional information about sample and procedure.)

6.2. Results

6.2.1. Risk Preferences (H2). Wealth profiles with positive net worth all reflect the same net wealth because they only differ by a constant added to both assets and debts. For instance, wealth profile B (44; 8) can be obtained by adding a constant of 3 to the asset and debt portions of wealth profile A (41; 5). In line with sensitivity to gain-loss ratio, we find that the correlation between asset-debt ratio and average rank is perfect when profiles have positive net worth (Spearman's $\rho = -1$).[4] Or in other words, the rank for wealth profiles with smaller assets and debts is lower (i.e., more favorable) than the rank for wealth profiles with larger assets and debts. This result supports our contention that people are more sensitive to variation in losses than to equal variation in gains, and thus risk averse, when expected value is positive (H2A).

Similarly, wealth profiles with negative net worth all reflect the same net wealth because they only differ by a constant added to both assets and debts. For instance, wealth profile K (7; 43) can be obtained by adding a constant of 5 to the asset and debt portions of wealth profile J (2; 38). In line with sensitivity to gain-loss ratio, we find that the correlation between asset-debt ratio and average rank is close to perfect when profiles have negative net worth (Spearman's $\rho = -0.92$, $p < 0.001$). Or in other words, the rank for wealth profiles with larger assets and debts is lower (i.e., more favorable) than the rank for wealth profiles with smaller assets and debts. This result supports our contention that people are more sensitive to variation in gains than to equal variation in losses, and thus risk seeking, when expected value is negative (H2B).

6.2.2. Preference Extremity (H4). If participants are sensitive to asset-debt ratio and the asset-debt ratios of wealth profiles are hard to discriminate, one would expect that the ranking of wealth profiles is inconsistent across participants. For instance, participants would rank different wealth profiles as most desirable and different wealth profiles as least desirable. As a consequence, the rank of wealth profiles averaged across participants should be relatively similar. In the extreme, if participants would disagree completely, the average rank of all wealth profiles would be 5. Thus, in statistical terms, when wealth profiles are hard to discriminate the variance of the average ranks of the wealth profiles should be relatively low. In contrast, if participants are sensitive to asset-debt ratio and the asset-debt ratios of wealth profiles are easy to discriminate, one would expect that the ranking of wealth profiles is more consistent across participants. For instance, participants would rank the same wealth profile as most desirable and the same wealth profile as least desirable. In the extreme, if all participants rank the wealth profiles in the same way, the average ranks would be 1, 2, 3, 4, 5, 6, 7, 8, and 9. Thus, in statistical terms, when wealth profiles are easy to discriminate the variance of the average ranks of the wealth profiles should be relatively high. We build on this reasoning to carry out a test of H4, which predicts an effect of expected value domain on gain-loss ratio discriminability.

If most people ranked the profiles based on asset-debt ratios then we should find greater variability in the ranking of wealth profiles when assets are larger than debts (i.e., equivalent to the positive expected value domain) than when assets are smaller than

[4] Note that the correlation is negative because lower average ranks indicate more desirable profiles.

debts (i.e., equivalent to the negative expected value domain). In support of this contention, we observe more variability in the ranking of wealth profiles when net worth is positive than when net worth is negative (F-test of equality of variances: $F(8, 8) = 6.99$, $p < 0.01$). This is partly because assets and debts have a wider range of 118 for profiles with positive net worth (assets range from 36 to 154 and debts range from 0 to 118) and narrower range of 63 for profiles with negative net worth (assets range from 0 to 63 and for debts range from 36 to 99) but that is not the only reason. Also when considering a subset of profiles such that the range for assets and debts is about the same when net worth is positive (i.e., excluding profiles 7–9 such that assets and debts have a range of 53 with assets ranging from 41 to 94 and debts ranging from 5 to 58) and when net worth is negative (i.e., excluding profile 1 such that assets and debts have a range of 56 with assets ranging from 7 to 63 and debts ranging from 43 to 99), there is more variability in the ranking of wealth profiles when net worth is positive than when net worth is negative ($F(5, 7) = 12.07$, $p < 0.01$). In other words, people discriminate less between wealth profiles when assets are smaller than debts than when assets are larger than debts. The asymmetry in the ranking of wealth profiles with asset-debt ratios smaller versus larger than 1 is in line with the asymmetries we found in Study 1 for choice shares and reaction times and the asymmetry we found in Study 3 for attractiveness ratings. This pattern of results provides further support for H4 and is uniquely predicted by sensitivity to gain-loss ratio.

7. Study 6

Study 5 suggests that people's behavior is consistent with gain-loss ratio when gains and losses are certain. In Study 6, we examine whether people's choices are consistent with gain-loss ratio when probabilities are unequal across decision alternatives, that is, when the probability of winning is different across options and when the probability of losing is different across options.

7.1. Method

7.1.1. Participants, Design, and Procedure. One hundred eleven business undergraduates at a U.S. university participated in this study in exchange for extra course credit (57 females, $M_{\text{age}} = 20.00$, $SD = 1.93$). Participants were asked to choose 24 times between two mixed gambles. Data from one participant were eliminated before performing the analyses (this participant took less than one second to decide on more than 40% of trials), leading to a final sample size of 110. The gambles were sampled (without replacement) from an (1) outcome space with gains and losses ranging from \$5 to \$95 with increments of \$5 and (2) a probability space ranging from 0.05 to 0.95 with increments of 0.05.

When probabilities are allowed to vary, it is not possible to uniquely identify the parameters of prospect theory's value function (Nilsson et al. 2011, Prelec 1998, Wu and Markle 2008). Because the pattern of results predicted by gain-loss ratio implies more atypical parameter values for prospect theory when gambles have negative expected value, we decided to restrict the study to gambles with negative expected value. In Study 1 we found that gain-loss ratio has lower predictive ability when expected value is negative than when it is positive. As a result, gambles with negative expected value provide an especially conservative test of whether gain-loss ratio can account for choices between mixed gambles even when probabilities are allowed to vary. In total, the data set consists of 2,640 decisions. For each participant, gains were presented before losses for half of decisions and losses were presented before gains for the other half of decisions.

7.1.2. Sampling Procedure. For each participant, 24 gamble pairs were randomly sampled from the outcome space, subject to four restrictions:

- The expected value of the gambles was not zero (that is, the expected gain was never equal to the expected loss).
- The gain portions varied across gambles (that is, gains were never equal).
- The loss portions varied across gambles (that is, losses were never equal).
- The probabilities varied across gambles (that is, the probability of winning and losing was different).

Similar to Study 1, participants were presented with four types of gamble pairs. The first category consists of gamble pairs for which gain-loss ratio and expected value favor the same option. The second category consists of gambles for which gain-loss ratio and expected value are dissociated. If gain-loss ratio drives choice, participants will incur suboptimal monetary outcomes when presented with gamble pairs from category 2 (H1B) but not when presented with gamble pairs from category 1 (H1A). The third category consists of gambles with equal expected value. This category affords a clean test of participants' preference for risk (H2B). Holding constant expected value, risk seeking implies choosing the gamble with higher outcome variance. The fourth category consists of gambles with equal gain-loss ratio. We intended to replicate the analysis we did in Study 1 where we compared the extremity in choice shares for this category of gamble pairs with the extremity in choice shares for the other three categories. However, the sampling procedure resulted in a data set where virtually all gamble pairs were presented only once (see also §7.2). For each unique gamble pair, the extremity index is 0.5 ($0.5 = |1-0.5| = |0-0.5|$). It is thus impossible to test H3. Every participant was presented with six gamble pairs sampled from each of the categories above. For half of the gamble pairs in each category, the gains were presented first. For the other half of gamble pairs, the losses were presented first.

7.2. Results

Because the large majority of gamble pairs was presented only once (2,622 out of 2,640), we will use decisions as a unit of analysis (i.e., 2,640 observations) instead of gamble pairs (i.e., 2,622 observations). For each of the 2,640 choices, gain-loss ratio makes a prediction (i.e., choose gamble *L*, choose gamble *R*, choose gamble *L* or gamble *R*). The accuracy of gain-loss ratio was scored as 1 if gain-loss ratio accurately predicted choice and as 0 if gain-loss ratio did not accurately predict choice. Accuracy was scored as a missing value if gain-loss ratio was not diagnostic for the particular gamble pair (i.e., choose gamble *L* or gamble *R*). We computed an accuracy index by averaging over the 1,980 decisions for which gain-loss ratio is diagnostic. Gain-loss ratio accurately predicted choice 68% of the times ($SD = 0.47$).

This accuracy score underestimates the accuracy score that would be observed if gambles had been randomly sampled from the outcome space without restrictions pertaining to the number of gamble pairs sampled from each category. Because gamble pairs were not sampled uniformly from the outcome space, some categories of gamble pairs are overweighted by doing the analysis at the decision level. Weighting accuracy scores for the various categories of gamble pairs in Study 6 instead by their natural frequency of occurrence yields an accuracy score of 79%. This score can be directly compared and is identical to the accuracy score for gambles with negative expected value in Study 1 (where we did the analysis at the gamble level and thus all gamble pairs are weighted by their natural frequency of occurrence). In sum, the findings are consistent with the idea that gain-loss ratio drives decision making, even when probabilities are different from 0.5 and unequal across gambles.

7.2.1. Expected Monetary Value (H1). Gain-loss ratio and expected value favor the same option for 660 decisions (see category 1). The likelihood of choosing the gamble with the higher expected value averaged across these pairs is significantly higher than chance ($M = 0.82$, $SD = 0.38$, $t(659) = 21.87$, $p < 0.001$). Thus, in support of H1A, when two gambles are ranked the same based on expected value and gain-loss ratio, people favor gambles with higher monetary outcomes. Gain-loss ratio and expected value are instead dissociated for 660 decisions (see category 2). The likelihood of choosing the gamble with the higher expected value (and thus lower gain-loss ratio) averaged across these choices is significantly lower than chance ($M = 0.44$, $SD = 0.50$, $t(659) = 2.98$, $p < 0.01$). Thus, in support of H1B, when two gambles are ranked differently based on expected value and gain-loss ratio, people favor gambles with suboptimal monetary outcomes.

7.2.2. Risk Preferences (H2B). To assess risk preferences, we analyzed choices when gambles have equal expected value. This is the case for 660 decisions (see category 3). Recall that all gambles in this study have negative expected values. The likelihood of choosing the more risky gamble (the gamble with higher outcome variance) is significantly higher than chance ($M = 0.66$, $SD = 0.47$, $t(653) = 8.62$, $p < 0.001$). To examine sensitivity to gains and losses more generally, we computed the difference between expected gains ($\Delta g = p_{gL}g_L - p_{gR}g_R$) and the difference between expected losses for each gamble pair ($\Delta l = p_{lL}(-l_L) - p_{lR}(-l_R)$). We then regressed choice (*L* or *R*) on Δg and Δl. This analysis allows us to use all 2,640 decisions and is similar to our analyses in Studies 1 and 3, except that here we use logistic regression. The absolute values for the 95% confidence intervals for the effect of Δg (95% CI: $[0.086, 0.108]$) and Δl (95% CI: $[-0.036, -0.047]$) were nonoverlapping. In other words, choice was affected more by variation in gains than by variation in losses.

7.2.3. Additional Analyses. *Gain-Loss Ratio vs. Ratio of First over Second Outcome.* In previous studies we always presented the gain before the loss. If people shift from taking the gain-loss ratio to the loss-gain ratio when the loss is presented first, we would expect to find a difference such that choices are more extreme (i.e., decisions are more likely to be consistent with payoff ratio) when the loss is presented first. This is because in the negative expected value domain the gain-loss ratio is compressed between 0 and 1, and the loss-gain ratio ranges between 1 and $+\infty$. To examine this possibility, we estimated a logistic regression model in which we analyzed the accuracy of gain-loss ratio for each decision (0 or 1) as a function of whether the gain or the loss was presented first. There was no significant effect of presentation order suggesting that whether gains or losses are displayed first has no impact on preference extremity ($\chi^2 = 0.14$, $p = 0.71$). In sum, given also the support for H4–H7 in Study 1 (i.e., the findings about the greater discriminability of gain-loss ratio in the positive than negative expected value domain), we can conclude that people are not basing their decisions on loss-gain ratio or on the ratio of the first over the second outcome. Instead, they base their decisions on gain-loss ratio.

Prospect Theory. We estimated prospect theory parameter values after transforming objective probabilities according to the probability weighting function specified in §1.4. Because the curvature in the probability weighting function (γ) cannot be identified uniquely from the curvature in the value function (α), we follow Wu and Markle (2008) and set γ to 0.55. We thus estimate three free parameters ($\alpha = \beta, \lambda$, and μ). The best-fitting parameter values are $\alpha = \beta = 0.51$ (95% CI: [0.49, 0.54]), $\lambda = 0.71$(95% CI: [0.65, 0.77]), and $\mu = 1.19$(95% CI: [0.99, 1.39]). In §1.4 (see also Appendix C), we presented the results of a simulation study in which we estimated prospect theory parameters based on a choice data set generated by gain-loss ratio maximization. We estimated parameters based on gambles with positive and negative expected values. To better evaluate the results of Study 6, we estimated prospect theory parameters again now using only the gambles with negative expected value in the simulated choice data set. When expected value is negative, gain-loss ratio maximization implies greater sensitivity to gains (see §1.2). In line with this, we find a loss-aversion parameter smaller than 1 (i.e., gain seeking) when prospect theory parameters are estimated based on gambles with negative expected value only. In particular, the best-fitting parameter values obtained in Study 6 ($\alpha = 0.51$ and $\lambda = 0.71$) are very similar to the ones obtained based on the gambles with negative expected value in the simulated choice data set. For instance, when randomness is moderate ($\mu = 1$): $\alpha = 0.55$ and $\lambda = 0.67$. This additional analysis provides further support for gain-loss ratio maximization in the context of choice between mixed gambles with different probabilities of winning and losing.

8. Study 7

When mixed gambles feature a certain loss in combination with a low-probability gain, prospect theory with standard parameter values predicts a greater preference for gambles with higher outcome variance. This is due to the inverse S-shaped nature of prospect theory's probability weighting function, which implies overweighting of small probabilities. For instance, consider the following three insurance options each involving coverage for a 1% chance of lost luggage (i.e., a low-probability gain) and a premium (i.e., a sure loss): *LOW* (100, 0.01; −9, 1), *MED* (400, 0.01; −12, 1), *HIGH* (700, 0.01; −15, 1). Prospect theory with standard parameter values ($\alpha = \beta = 0.88$, $\lambda = 2.25$, and $\gamma = 0.55$) predicts the following ranking: $PT_{\text{LOW}} = -11.54 < PT_{\text{MED}} = -6.44 < PT_{\text{HIGH}} = -2.13$. Sensitivity to gain-loss ratio predicts the same ranking but for a different reason. Specifically, for options with the same negative expected value, gain-loss ratio increases with the magnitude of gains and losses, which should lead to a preference for options with larger outcome variance (see §1.2), that is for insurances with higher premiums and more coverage.

In Study 7, we ask participants to evaluate insurance options that feature a certain premium and a low-probability coverage amount. Although the design of this study does not allow disentangling gain-loss ratio maximization from prospect theory, we think this study is important nevertheless. The context of insurance decisions is a mixed gamble situation of substantive importance to consumers and the previous studies demonstrated that decisions between mixed gambles are oftentimes not aligned with prospect theory. It is thus valuable to empirically test whether people indeed have a preference for insurance options with higher coverage and premiums.

8.1. Method

We asked 115 respondents from Amazon Mechanical Turk to imagine they wanted to insure their luggage against loss while traveling (we did not ask respondents to indicate their age and gender in this study). We told participants that there is a 1% chance (1 out of 100) that their luggage would be lost and then presented them with two insurance options. Participants rated the relative attractiveness of the insurance options on a scale from −4 (*the first option is more attractive*) to +4 (*the second option is more attractive*). We presented about half of participants with a low-variance option (100, 0.01; −9, 1) and a medium-variance option (400, 0.01; −12, 1). The other half of participants was presented with the same medium-variance option and a high-variance option (700, 0.01; −15, 1). We counterbalanced presentation order such that sometimes the option with the higher outcome variance was presented first and other times the option with the lower outcome variance was presented first. After rating relative attractiveness, we asked participants to report the coverage of their most preferred option. Nine participants were unable to accurately answer this question and were excluded before data analysis.

8.2. Results

The three insurance options have identical expected values ($EV_{\text{LOW}} = EV_{\text{MED}} = EV_{\text{HIGH}} = -8$) but different gain-loss ratios ($GLR_{\text{LOW}} = 0.11, GLR_{\text{MED}} = 0.33, GLR_{\text{HIGH}} = 0.47$). If people care about gain-loss ratio, they should prefer the high-variance option over the medium-variance option and the medium-variance option over the low-variance option. Prospect theory with typical parameter values predicts a behavioral result that is very consistent with gain-loss ratio maximization because of probability weighting (i.e., the inverse S-shaped nature of its probability weighting function). Maximizing gain-loss ratio implies the same behavioral result but for a different reason: the relationship between outcome magnitude and gain-loss ratio is nonlinear.

We first transformed relative attractiveness ratings such that scores above zero indicate a preference for the more risky option. In line with H2B, participants rated the option with higher outcome variance as most attractive regardless of whether they were presented with the low-variance and the medium-variance options ($M = 3.03$, $SD = 1.80$, $t(56) = 12.71$, $p < 0.001$) or with the medium-variance and the high-variance options ($M = 2.16$, $SD = 2.31$, $t(49) = 6.55$, $p < 0.001$). Note that when expected value is negative, gain-loss ratio increases in a decelerating way when the gain and loss portions of a gamble are increased with the same constant. As a consequence, the difference in gain-loss ratio between the low-variance option and the medium-variance option (0.22) is larger than the difference in gain-loss ratio between the medium-variance option and the high-variance option (0.13). Decision makers relying on gain-loss ratio should thus differentiate more between the low-variance and the medium-variance option than between the medium-variance and the high-variance option. In line with this, participants discriminated more between the low-variance and the medium-variance options than between the medium-variance and the high-variance options (3.03 versus 2.16: $t(104) = 2.18$, $p < 0.05$).

9. General Discussion

9.1. Summary of Findings

People often face situations that involve a trade-off between gains and losses. Whereas the most influential normative and descriptive theories of decision making assume that people integrate the (psychological) consequences of mixed gambles in an additive way, we propose instead that people attend to the rate of exchange between positive and negative outcomes. They care about gain-loss ratio, or efficiency. Although efficiency is an important notion in finance and management (e.g., return on investment), it has not been considered in the judgment and decision-making literature as a carrier of value. The most important contribution of the current paper is to demonstrate that people display a tendency to favor decision options with larger gain-loss ratios.

We predicted that people favor options with higher expected monetary outcomes when gain-loss ratio and expected value are aligned (H1A) but incur suboptimal monetary outcomes whenever gain-loss ratio and expected value are dissociated (H1B), risk aversion for mixed gambles with positive expected value (H2A) but risk seeking for mixed gambles with negative expected value (H2B), less extreme preferences when gain-loss ratio is not diagnostic (H3), and less extreme preferences and longer decision times for gambles with negative expected value than for gambles with positive expected value (H4–H7). The results of seven studies (five new experiments and two reanalyses of recently published findings) are consistent with these predictions. Sensitivity to gain-loss ratio is reflected in choices between mixed gambles (Studies 1, 6, and 7), attractiveness ratings of mixed gambles presented in isolation (Studies 2 and 3), decisions of whether to accept or reject mixed gambles (Study 4), and the ranking of wealth profiles that are mixed in terms of assets and debts (Study 5). We find that people are sensitive to gain-loss ratio when gains and losses are certain (Study 5), when probabilities for uncertain gains and losses are equal to 0.5 (Studies 1–4), when probabilities for uncertain gains and losses are different from 0.5 and unequal across gambles (Study 6), and when the probability of gains is very small but losses are certain (Study 7). Across studies, we examined the viability of several alternative accounts for the data.

Future research should explore the psychological antecedents of reliance on gain-loss ratio. In particular, there may be heterogeneity in sensitivity to gain-loss ratio across individuals (e.g., rational versus experiential thinking styles; Pacini and Epstein 1999), tasks characteristics (e.g., time pressure; Payne 1982), social incentives (e.g., outcome versus process accountability; de Langhe et al. 2011), and financial stakes (e.g., Payne 1982).

9.2. Implications

9.2.1. Prospect Theory. Mixed gambles are an understudied area of research in decision making under risk. This dearth of research is especially problematic because the relatively few papers dedicated to mixed gambles have found prospect theory wanting. Wu and Markle (2008) document several mixed gamble pairs for which mixed gamble *L* is preferred over mixed gamble *R*, but the gain and loss portions of gamble *R* are preferred over the gain and loss portions of gamble *L*. Such gamble pairs violate the assertion of prospect theory (and any other additive utility model) that the overall value of a gamble can be expressed as an additive function of its positive and negative components (i.e., gain-loss separability; see also Birnbaum and Bahra 2007, Por and Budescu 2013). To account for this violation while retaining the fundamental properties of prospect theory (e.g., the notions of a probability weighting function, a value function over gains and losses, loss aversion, and additive integration of subjective values), the authors suggest that people may be less sensitive to differences in objective probabilities when choosing between mixed-domain gambles than when choosing between single-domain gambles. By adding another parameter to the model, the curvature in the probability weighting function is allowed to vary depending on whether the gambles have mixed outcomes versus not. The studies in this paper confirm the specificity of mixed gambles but, instead of incrementally adjusting prospect theory, we suggest to reconsider the fundamental assumption of additive integration. We propose that a dual process model is needed that assumes additive integration for single-domain gambles and multiplicative integration for mixed gambles (see Study 2). This has implications for the estimation and interpretation of prospect theory's parameters. First, one should not estimate loss aversion in the context of mixed gambles conditional on estimates obtained from single-domain gambles (e.g., Abdellaoui et al. 2007). Second, even when estimating prospect theory's parameters based on mixed gambles only, the parameters related to the steepness and curvature of the value function may not stem from loss aversion and decreasing marginal sensitivity but from the multiplicative integration of gains and losses.

Loss Aversion. Research on prospect theory suggests that losses are weighted more than twice as much than corresponding gains ($\lambda = 2.25$), which "explains the extreme reluctance to accept mixed prospects" (Tversky and Kahneman 1992, p. 316). Our estimates for λ are more modest and lie close to the values that would be expected if decision makers value mixed gambles based on gain-loss ratio (see §1.4). The relatively few papers on mixed gambles also find little or no loss aversion (Battalio et al. 1990, Erev et al. 2008, Ert and Erev 2008, Kermer et al. 2006, Nilsson et al. 2011). Little or no loss aversion in the context of mixed gambles has two related implications. First, prospect theory predicts risk aversion for mixed gambles with equal odds of winning and losing based on loss aversion (Benartzi and Thaler 1999, Thaler et al. 1997). Sensitivity to gain-loss ratio also predicts risk aversion for gambles with positive expected value. Although the prediction of risk aversion for gambles with positive expected value is in line with prospect theory, gain-loss ratio provides a conceptual underpinning for this prediction that is independent of loss aversion. Moreover, sensitivity to gain-loss ratio predicts risk seeking instead of risk aversion for mixed gambles with negative expected value. Second, loss aversion implies that losses are generally weighted more than gains. Little or no loss aversion in combination with sensitivity to gain-loss ratio instead implies greater sensitivity to variation in losses for gambles with positive expected value but greater sensitivity to variation in gains for gambles with negative expected values. The empirical results reported in this paper pertaining to risk preferences and the weighting of gains versus losses follow from sensitivity to gain-loss ratio.

Decreasing Marginal Sensitivity. Prospect theory traces the curvature in the value function to the psychophysical principle of decreasing marginal sensitivity according to which people's ability to discriminate changes in a physical stimulus diminishes as the magnitude of the stimulus increases. A difference of a constant magnitude (say \$10) seems subjectively smaller when it is applied to large magnitudes (say \$110) than when it is applied to small magnitudes (say \$10). Because this applies symmetrically for gains and losses the value function is concave over gains and convex over losses. Hsee and Rottenstreich (2004) instead propose that the curvature in the value function can be traced to two different ways of thinking, one more affective and one more cognitive in nature. (See Rottenstreich and Hsee 2001 for a similar account for the curvature in the probability weighting function.) Evaluation based on feelings leads to scope insensitivity and value functions that are a step function of magnitude. Evaluation based on calculation leads to scope sensitivity and value functions that are a linear function of magnitude. Sometimes evaluation is based on affect and other times it is based on calculation. The combination of a step function and a linear function implies a nonlinear and decelerating function and thus a concave value function over gains and a convex value function over losses. Although the accounts based on psychophysics and affect are very different, they share the assumption that the valuation of gains and losses *an sich* is nonlinear.

We suggest that for mixed gambles the curvature in the value function may be a side effect of the multiplicative integration rule that people use when combining gains and losses. If the value function over gains and losses is in fact linear and people multiplicatively integrate gains and losses, the additive deconstruction of overall evaluations and choices into gains and losses will reveal a nonlinear value function over gains and losses. In other words, a decision maker who values options linearly in terms of gain-loss ratio will appear to an observer who assumes additive integration of expected outcomes as having an S-shaped value function. Thus, a value function with a pronounced S-shape could be the result, not of valuation by feelings, but of valuation by calculation according to gain-loss ratio. Future research should examine how valuation by feeling versus calculation affects sensitivity to gain-loss ratio.

Probability Weighting. For 50–50 gambles with negative expected value, prospect theory with typical parameter values predicts very different behavioral results from sensitivity to gain-loss ratio. However, when expected value is negative and there is a low probability of receiving a gain, prospect theory with typical parameter values predicts a behavioral result that is very consistent with gain-loss ratio maximization. This is due to the inverse S-shaped nature of the prospect theory's probability weighting function that implies overweighting of small probabilities. In Study 7, participants ranked insurance options consistent with the coverage-premium ratio. Given the evidence in support for gain-loss ratio maximization across our studies, these findings highlight the possibility that a pattern of results consistent with the probability weighting function of prospect theory may in fact emerge as a result of gain-loss maximization.

9.2.2. Discriminability and Evaluability. Gain-loss ratios for gambles with positive expected value vary between 1 and $+\infty$, whereas gain-loss ratios for gambles with negative expected value vary between 0 and 1. Differences between gambles with negative expected value in terms of gain-loss ratio are thus compressed in a smaller range and harder to discriminate. We find that this asymmetry is consistently reflected in evaluation and choice and we believe that it provides unique evidence for the role played by gain-loss ratio in the context of mixed gambles. In Study 1, gain-loss ratios differ more between gambles when expected value is positive than when it is negative and this resulted in more extreme choice shares as well as shorter decision times. Lending additional credibility to the role of gain-loss ratio discriminability, the effect of expected value domain on choice shares and decision time was mediated by the absolute difference between the two gambles' gain-loss ratios. The same asymmetric pattern between gambles with gain-loss ratios larger versus smaller than one was observed in Study 3 where attractiveness ratings for gambles presented in isolation differed more for gambles with positive expected value than for identical gambles with inverted gain and loss portions. And the same asymmetry was manifest in Study 5 where the ranking of wealth profiles was more pronounced for individuals with positive than for individuals with negative net worth.

Another way in which individuals can express the perceived utility of a gamble is by expressing a judgment of its attractiveness when the gamble is presented in isolation. Joint and separate evaluation modes do not necessarily lead to the same ranking of gambles (Hsee and Zhang 2010). Not many dimensions are evaluable in a single evaluation context. The ones that are tend to be central to people's well-being such as temperature or amount of sleep (physiological dimensions), or social connectedness (a fundamental human motive; Hsee and Zhang 2010). A common assumption in ecology is that natural selection favors organisms that harvest food efficiently (Gallistel 1990, Schoener 1971, Smith 1979), where greater efficiency implies a higher ratio of energy acquired over time or energy expended. For instance, shore crabs (*carcinus maenas*) choose mussel sizes that maximize the ratio between mussel energy content and handling time (i.e., gain-loss ratio; Elner and Hughes 1978). If ecological fitness of organisms is based on maximizing return on investment, it is possible that multiplicative integration is a hardwired component of human decision making in mixed outcome situations.

Acknowledgments
The authors thank three anonymous reviewers for their thorough and insightful comments, and the associate editor and department editor for their clear guidance in shaping this paper. The authors also thank Abigail Sussman, Eldar Shafir, Boaz Keysar, Sayuri Hayakawa, and Sun Gyu An for generously sharing their data. The authors are grateful for feedback provided on earlier drafts of this paper by John Lynch, Stijn van Osselaer, and Robert Rooderkerk.

Appendix A. Dissociation Between Gain-Loss Ratio and Expected Value

Consider mixed gambles L $(g_L, p; l_L)$ and R $(g_R, p; l_R)$.[5] As can be seen in Figure 1, gamble R lies below the line indicating all gambles that are equivalent to gamble L in terms of gain-loss ratio (dashed line) and it lies above the line indicating all gambles that are equivalent to gamble L in terms of expected value (solid line). It can be shown that

- $g_L/(-l_L)$ is the slope of the line indicating all gambles R in the outcome space that are equal in gain-loss ratio to gamble L, because $GLR_L = (pg_L)/[(1-p)(-l_L)] \Rightarrow g_L = [(1-p)/p]GLR_L(-l_L) \Rightarrow g_L = (g_L/(-l_L))(-l_L)$;
- $(1-p)/p$ is the slope of the line indicating all gambles R in the outcome space that are equal in expected value to gamble L, because $EV_L = pg_L - (1-p)(-l_L) \Rightarrow g_L = (1/p)EV_L + [(1-p)/p](-l_L)$, where $(1/p)EV_L$ is the intercept of the function relating $-l_L$ to g_L and $(1-p)/p$ is the slope of the function relating $-l_L$ to g_L;
- for $EV_L > 0$, the slope of the line indicating gambles R equal in gain-loss ratio to gamble L is steeper than the slope of the line indicating gambles R equal in expected value to gamble L, because $EV_L = pg_L - (1-p)(-l_L) > 0 \Rightarrow (1-p)/p < g_L/(-l_L)$;
- for $EV_L < 0$, the slope of the line indicating gambles R equal in gain-loss ratio to gamble L is less steep than the slope of the line indicating gambles R equal in expected value to gamble L, because $EV_L = pg_L - (1-p)(-l_L) < 0 \Rightarrow (1-p)/p > g_L/(-l_L)$.

[5] For simplicity, and consistent with much research on risky decision making, we focus on the case in which the probabilities of positive and negative outcomes sum up to one and are equal across gambles. It is possible to generalize the theoretical analysis to the case in which the probabilities of positive and negative outcomes are independent and different across gambles. However, in this case the increase in the number of free parameters leads to greater complexity. In particular, the implications for suboptimal monetary outcomes and risk preferences become contingent on trade-offs between probabilities and payoffs.

Maximizing gain-loss ratio leads to choosing the option with the lower expected value whenever gain-loss ratio and expected value are dissociated, that is one gamble has a better gain-loss ratio than the other but a worse expected value, for example when $GLR_L > GLR_R$ and $EV_L < EV_R$. The slope of the line relating gamble L to any gamble R in the outcome space is $(g_R - g_L)/[(-l_R) - (-l_L)]$. Therefore, reliance on gain-loss ratio leads to suboptimal monetary outcomes whenever

- for $EV_L > 0$ and $EV_R > 0$, $(1-p)/p < (g_R - g_L)/[(-l_R) - (-l_L)] < g_L/(-l_L)$ (see Figure 1(a));
- for $EV_L < 0$ and $EV_R < 0$, $g_L/(-l_L) < (g_R - g_L)/[(-l_R) - (-l_L)] < (1-p)/p$ (see Figure 1(b));
- for $EV_L < 0$ and $EV_R > 0$, it is not possible that $EV_L < EV_R$ and $GLR_L > GLR_R$ (for $EV_L < 0$, $(1-p)/p > g_L/(-l_L)$; for $EV_R > 0$, $(1-p)/p < g_R/(-l_L)$. As a result, $g_L/(-l_L) < g_R/(-l_R) \Rightarrow GLR_L < GLR_R$, but $GLR_L > GLR_R$.

Appendix B. Proof of H2

For any mixed gamble, it is possible to find two constants c_g and c_l that can be added to the gain and loss portions of a gamble without changing its expected value. Formally, consider c_g and c_l where $c_l = (c_g p)/(1-p)$. Adding c_g to the gain of a gamble and c_l to the loss does not affect the expected value of the gamble (proof: $pg - (1-p)(-l) = p(g+c_g) - (1-p)[(-l)+c_l] \Leftrightarrow pg - p(g+c_g) = (1-p)(-l) - (1-p)[(-l)+c_l] \Leftrightarrow p[g - (g+c_g)] = (1-p) \cdot [(-l) - [(-l)+c_l]] \Leftrightarrow p(-c_g) = (1-p)(-c_l) \Leftrightarrow (c_g p)/(1-p) = c_l$). Adding c_g to the gain of a gamble and c_l to the loss does, however, affect the gain-loss ratio of the gamble and the effect is systematically different depending on whether the expected value of the gamble is positive or negative.

When expected value is positive, increasing the gain with a constant c_g and the loss with a constant c_l results in a lower gain-loss ratio (proof: $(pg)/[(1-p)(-l)] > 1 \Leftrightarrow (pg)/(1-p) > (-l) \Leftrightarrow (pgc_g)/(1-p) > (-l)c_g \Leftrightarrow gc_l > (-l)c_g \Leftrightarrow gc_l + g(-l) > (-l)c_g + g(-l) \Leftrightarrow g[c_l + (-l)] > (-l)(c_g + g) \Leftrightarrow g[c_l + (-l)]p(1-p) > (-l)(c_g+g)p(1-p) \Leftrightarrow (pg)/[(1-p)(-l)] > [p(c_g+g)]/[(1-p)[c_l + (-l)]]$). Thus, when choosing between two gambles with equal positive expected value, maximizing gain-loss ratio leads to a preference for gambles with lower outcome variance, that is, risk aversion. This also implies that an increase in the expected value of a gamble with positive expected value is more impactful when the increase stems from a change in the loss portion of the gamble than when it stems from a change in the gain portion (proof: $(pg)/[(1-p)(-l)] < [p(g+c_g)]/[(1-p)(-l)] < (pg)/[(1-p)[(-l)-c_l]]$).

When expected value is negative, increasing the gain with a constant c_g and the loss with a constant $c_l$results in a higher gain-loss ratio (proof: $(pg)/[(1-p)(-l)] < 1 \Leftrightarrow (pg)/(1-p) < (-l) \Leftrightarrow (pgc_g)/(1-p) < (-l)c_g \Leftrightarrow gc_l < (-l)c_g \Leftrightarrow gc_l + g(-l) < (-l)c_g + g(-l) \Leftrightarrow g[c_l + (-l)] < (-l)(c_g+g) \Leftrightarrow g[c_l+(-l)]p(1-p) < (-l)(c_g+g)p(1-p) \Leftrightarrow (pg)/[(1-p)(-l)] < [p(c_g+g)]/[(1-p)[c_l+(-l)]]$). Thus, when choosing between two gambles with equal negative expected value, maximizing gain-loss ratio leads to a preference for gambles with higher outcome variance, that is, risk seeking. This also implies that a decrease in the expected value of a gamble with negative expected value is more impactful when the decrease stems from a change in the gain portion than when it stems from a change in the loss portion (proof: $(pg)/[(1-p)(-l)] > (pg)/[(1-p)[(-l)+c_l]] > [p(g-c_g)]/[(1-p)(-l)]$).

Appendix C. Simulation

We created a data set of 50,000 gamble pairs: $L(g_L, 0.5; l_L)$ and $R(g_R, 0.5; l_R)$. It is often impossible to identify parameters of the value function uniquely from those of the probability weighting function (Prelec 1998, Wu and Markle 2008) and in this study we thus assumed $p = 0.5$. We randomly sampled the gamble pairs from an outcome space that ranged from 0.5 to 10 with increments of 0.5. Because decision making is an inherently stochastic process (Mosteller and Nogee 1951), we generated the probabilities of choosing gamble L over gamble R according to a logistic function

$$P(L > R) = 1/[1 + \exp(-\mu[U(L) - U(R)])],$$

where $U(L)$ is the utility of gamble L based on its gain-loss ratio and $U(R)$ is the utility of gamble R based on its gain-loss ratio. The sensitivity parameter μ captures the sensitivity of choice shares to differences in utility and reflects the randomness in the choice process. If $\mu = 0$, then all choices would be decided by a coin toss ($P(L > R) = 0.5$ for all L and R). As $\mu \to \infty$, $P(L > R) \to 1$ when $U(L) > U(R)$, and $P(L > R) \to 0$ when $U(L) < U(R)$. For each gamble pair, we computed $P(L > R)$ for four different levels of randomness: $\mu = 10$, $\mu = 5$, $\mu = 1$, and $\mu = 0.5$. In sum, we created a data set with 50,000 gamble pairs and generated four probabilities for each gamble pair that indicate the likelihood of choosing gamble L over gamble R. These probabilities follow gain-loss ratio according to varying degrees of randomness. Then, for the four probability vectors, we estimated the logistic model above now determining the utilities of the gambles, $U(L)$ and $U(R)$, according to prospect theory (instead of gain-loss ratio) with $U(L) = pg_L^\alpha - \lambda(1-p)(-l_L)^\beta$ and $U(R) = pg_R^\alpha - \lambda(1-p)(-l_R)^\beta$. We thus estimated this model four times.[6]

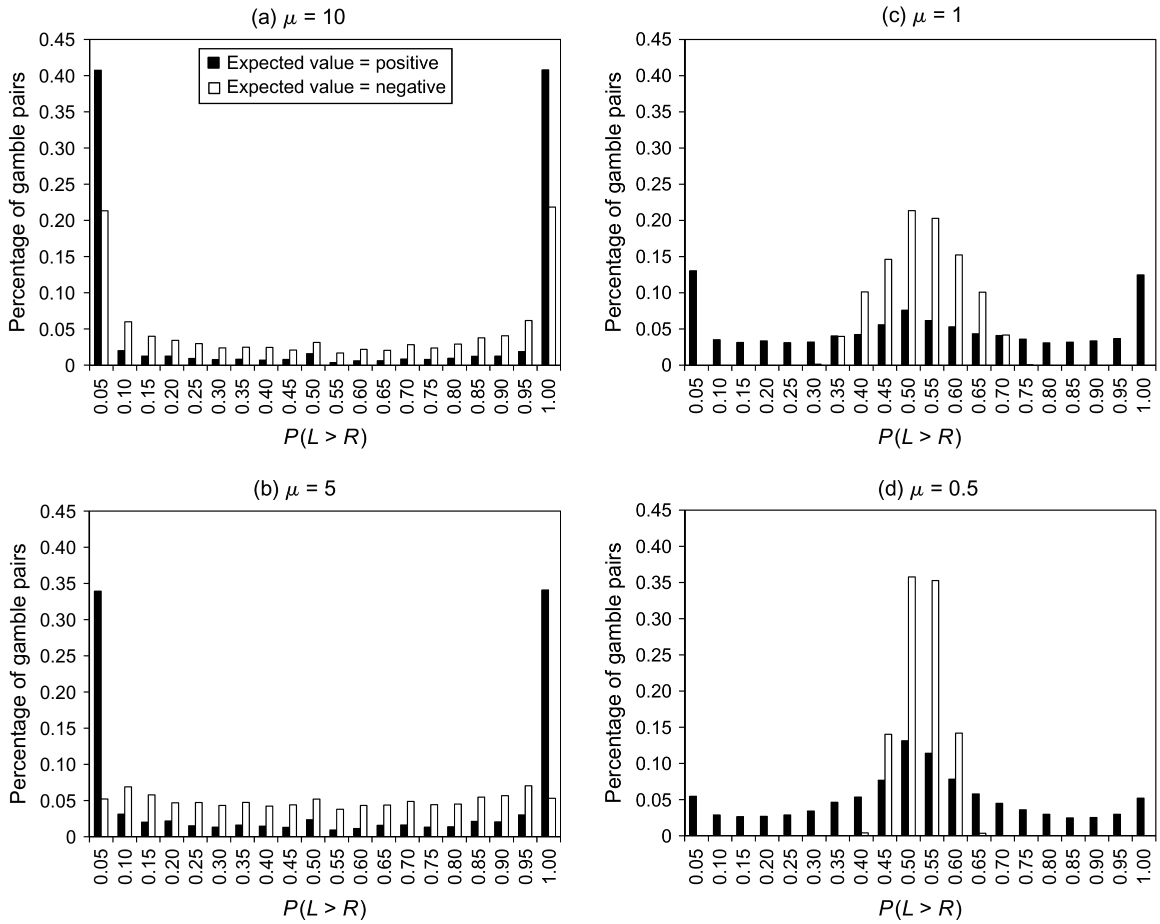
Table C.1 presents the estimated parameter values for prospect theory, the mean absolute deviation (*MAD*) between simulated choice shares stemming from gain-loss ratio maximization and predicted choice shares based on prospect theory, and the correlation (R) between simulated choice shares stemming from gain-loss ratio maximization and predicted choice shares based on prospect theory. When randomness is very low and thus probabilities are extreme (for $\mu = 10$), prospect theory mimics sensitivity to gain-loss ratio very well (*MAD* is low and R is high). However, (1) the estimated values for α and β lie close to 0 indicating extreme curvature in the value function and (2) the loss-aversion parameter λ lies close to 1 indicating that gains and

[6] For these analyses as well as in the remainder of this paper, we assume equal curvature in the value function for gains and for losses, i.e., $\alpha = \beta$. This reduces the number of free parameters in the choice model from four to three. We impose this equality restriction for two reasons. First, research has found equal curvature in the value function for gains and for losses (Tversky and Kahneman 1992). Second, the loss-aversion parameter λ is dramatically underestimated if the value function parameters α and β are allowed to vary freely because loss-averse behavior can be modeled with lower values for α than for β (Nilsson et al. 2011).

Table C.1 Results of the Simulation Study (See §1.4 and Appendix C)

Sensitivity to differences in gain-loss ratio	μ	$\alpha = \beta$	λ	*MAD*	*R*
$\mu = 10$	1447.734	0.012406	1.008605	0.0214659	0.99386
$\mu = 5$	297.4414	0.029303	1.029148	0.0382674	0.98731
$\mu = 1$	331.2129	0.005414	1.319243	0.0704566	0.94658
$\mu = 0.5$	59.01192	0.011646	1.658778	0.0652949	0.92110

Figure C.1 Choice Shares in the Positive vs. Negative Expected Value Domain for Gambles Sampled from the Outcome Space at the Four Different Levels of Randomness Used in the Simulation Study (See §1.4 and Appendix C)



Note. Choice shares are more extreme when expected value is positive than when expected value is negative because differences between gambles in terms of gain-loss ratio are more pronounced (see §1.3).

losses are weighted about equally. Prospect theory's ability to mimic sensitivity to gain-loss ratio deteriorates as randomness increases (for $\mu = 0.5$). Note that as randomness increases so does λ. Thus, stochastic choice based on a comparison of gain-loss ratios reveals a significant loss-aversion parameter in the absence of real loss aversion.

The simulation study also illustrates the effect of expected value domain on preference extremity (see §1.3). Figure C.1 plots the distribution of choice shares at the four different levels of randomness for gamble pairs with positive and negative expected value. At all levels of randomness (μ) choice shares are more extreme when expected value is positive than when expected value is negative. This is because the mean absolute difference between two gambles in terms of their gain-loss ratio is 2.36 in the positive expected value domain versus 0.29 in the negative expected value domain. Larger differences in gain-loss ratio have a stronger impact on choice shares than smaller differences in gain-loss ratio.

References

Abdellaoui M, Bleichrodt H, Paraschiv C (2007) Measuring loss aversion: A parameter-free approach. *Management Sci.* 53:1659–1674.

Anderson NH, Shanteau JC (1970) Information integration in risky decision making. *J. Experiment. Psych.* 84:441–451.

Bartels D (2006) Proportion dominance: The generality and variability of favoring relative savings over absolute savings. *Organ. Behav. Human Decision Processes* 100:76–95.

Bateman I, Dent S, Peters E, Slovic P, Starmer C (2007) The affect heuristic and the attractiveness of simple gambles. *J. Behav. Dec. Making* 20:365–380.

Battalio RC, Kagel JH, Jiranyakul K (1990) Testing between alternative models of choice under uncertainty: Some initial results. *J. Risk Uncertainty* 3:25–50.

Baumeister RF, Bratslavsky E, Finkenauer C, Vohs KD (2001) Bad is stronger than good. *Rev. General Psych.* 5:323–370.

Benartzi S, Thaler RH (1999) Risk aversion or myopia? Choices in repeated gambles and retirement investments. *Management Sci.* 45:364–381.

Birnbaum MH, Bahra JP (2007) Gain-loss separability and coalescing in risky decision making. *Management Sci.* 53:1016–1028.

Brandstatter E, Gigerenzer G, Hertwig R (2006) The priority heuristic: Making choices without trade-offs. *Psych. Rev.* 113:409–432.

Cartwright D (1941) Decision-time in relation to the differentiation of the phenomenal field. *Psych. Rev.* 48:425–442.

de Langhe B, van Osselaer SMJ, Wierenga B (2011) The effects of process and outcome accountability on judgment process and performance. *Organ. Behav. Human Decision Processes* 115: 238–252.

Elner RW, Hughes RN (1978) Energy maximization in the diet of the shore crab. *J. Animal Ecol.* 47:103–116.

Erev I, Ert E, Yechiam E (2008) Loss aversion, diminishing sensitivity, and the effect of experience on repeated decisions. *J. Behav. Decision Making* 21:575–597.

Ert E, Erev I (2008) The rejection of attractive gambles, loss aversion, and the lemon avoidance heuristic. *J. Econom. Psych.* 29: 715–723.

Festinger L (1943) Studies in decision: I. Decision-time, relative frequency of judgment and subjective confidence as related to physical stimulus difference. *Psych. Rev.* 32:291–306.

Gallistel CR (1990) *The Organization of Learning* (MIT Press, Cambridge, MA).

Goldstein WM, Einhorn HJ (1987) Expression theory and the preference reversal phenomena. *Psych. Rev.* 94:236–254.

Hsee CK (1998) Less is better: When low-value options are valued more highly than high-value options. *J. Behav. Dec. Making* 11:107–121.

Hsee CK, Rottenstreich Y (2004) Music, pandas, and muggers: On the affective psychology of value. *J. Experiment. Psych: Gen.* 133: 23–30.

Hsee CK, Zhang J (2010) General evaluability theory. *Perspect. Psych. Sci.* 5:343–355.

Hsee CK, Rottenstreich Y, Xiao Z (2005) When more is better: On the relationship between magnitude and subjective value. *Current Directions Psych. Sci.* 14:234–237.

Hsee CK, Loewenstein GF, Blount S, Bazerman MH (1999) Preference reversals between joint and separate evaluations of options: A review and theoretical analysis. *Psych. Bull.* 125: 576–590.

Kahneman D, Tversky A (1979) Prospect theory: An analysis of decision under risk. *Econometrica* 47:263–392.

Kermer DA, Driver-Linn E, Wilson TD, Gilbert DT (2006) Loss aversion is an affective forecasting error. *Psych. Sci.* 17:649–653.

Keysar B, Hayakawa SL, Gyu An S (2012) The foreign-language effect: Thinking in a foreign tongue reduces decision biases. *Psych. Sci.* 23:661–668.

Levy H, Markowitz HM (1979) Approximating expected utility by a function of mean and variance. *Amer. Econom. Rev.* 69:308–317.

Luce DR (2000) *Utility of Gains and Losses: Measurement-Theoretical and Experimental Approaches* (Erlbaum, New York).

March J, Shapira Z (1987) Managerial perspectives on risk and risk taking. *Management Sci.* 33:1404–1418.

Markowitz H (1952) Portfolio selection. *J. Finance* 7:77–91.

Meng X-L, Rosenthal R, Rubin DB (1992) Comparing correlated correlation coefficients. *Psych. Bull.* 111:172–175.

Meyer J (1987) Two-moment decision models and expected utility maximization. *Amer. Econom. Rev.* 77:421–430.

Mosteller F, Nogee P (1951) An experimental measurement of utility. *J. Political Econom.* 59:371–404.

Nilsson H, Rieskamp J, Wagenmakers E-J (2011) Hierarchical Bayesian parameter estimation for cumulative prospect theory. *J. Math. Psych.* 55:84–93.

Pacini R, Epstein S (1999) The relation of rational and experiential information processing styles to personality, basic beliefs, and the ratio-bias phenomenon. *J. Personality Soc. Psych.* 76:972–987.

Pascal B (1966) *Pensées* (A. J. Krailsheimer, translator) (Penguin, New York). [First published in 1670.]

Payne JW (1982) Contingent decision behavior. *Psych. Bull.* 2: 382–402.

Peters E, Vastfjall D, Slovic P, Mertz CK, Mazzocco K, Dickert S (2006) Numeracy and decision making. *Psych. Sci.* 17:407–413.

Por H, Budescu DV (2013) Revisiting the gain-loss separability assumption in prospect theory. *J. Behav. Dec. Making* 26: 385–396.

Preacher KJ, Hayes AF (2004) SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behav. Res. Meth. Instr. Comp.* 36:717–731.

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

Read D, Frederick S, Scholten M (2013) DRIFT: An analysis of outcome framing in intertemporal choice. *J. Experiment. Psych.: Learn. Memory, Cognition*. 39:573–588.

Rottenstreich Y, Hsee CK (2001) Money, kisses, and electric shocks: On the affective psychology of risk. *Psych. Sci.* 12:185–190.

Rozin P, Royzman EB (2001) Negativity bias, negativity dominance, and contagion. *Personality Soc. Psych. Rev.* 5:296–320.

Schoener TW (1971) Theory of feeding strategies. *Ann. Rev. Ecol. Systematics.* 2:369–404.

Slovic P, Lichtenstein S (1968) Relative importance of probabilities and payoffs in risk taking. *J. Experiment. Psych.* 3:1–18.

Slovic P, Finucane ML, Peters E, MacGregor DG (2004) Risk as analysis and risk as feelings: Some thoughts about affect, reason, risk, and rationality. *Risk Anal.* 24:311–322.

Smith EA (1979) Human adaptation and energetic efficiency. *Human Ecol.* 7:53–74.

Sussman AB, Shafir E (2012) On assets and debt in the psychology of perceived wealth. *Psych. Sci.* 23:101–108.

Thaler RH, Tversky A, Kahneman D, Schwartz A (1997) The effect of myopic loss aversion on risk taking: An experimental test. *Quart. J. Econom.* 112:647–661.

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

Von Neumann J, Morgenstern O (1944) *Theory of Games and Economic Behavior* (Princeton University Press, Princeton, NJ).

Wright JH (2001) The influence of absolute differences and relative sifferences on unidimensional difference judgments. Unpublished doctoral dissertation, University of Chicago, Chicago.

Wu G, Gonzalez R (1996) Curvature of the probability weighting function. *Management Sci.* 42:1676–1690.

Wu G, Markle AB (2008) An empirical test of gain-loss separability in prospect theory. *Management Sci.* 54:1322–1335.

Wu G, Zhang J, Gonzalez R (2004) Decision under risk. Koehler DJ, Harvey N, eds. *Blackwell Handbook of Judgment and Decision Making* (Blackwell, Malden, MA), 399–423.

Yechiam E, Hochman G (2013) Losses as modulators of attention: Reviews and analysis of the unique effects of losses over gains. *Psych. Bull.* 139:497–518.