Boundary Conditions for the Positive Skew Bias

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Abstract

Gambles that involve a large but unlikely gain coupled with a small but likely loss—like a lottery ticket—are known as positively-skewed. There is evidence that people tend to prefer these positively skewed choices, leading to what is called a positive-skew bias. In this study, we attempt to better understand under what conditions people are more drawn toward positively skewed, relative to symmetric, gambles. Based on the animal literature, there is reason to believe that preference for skewed gambles is dependent on the strength of the skew, with a greater preference for more strongly skewed options. In two online studies (Study 1: N = 209; Study 2: N = 210), healthy participants across the lifespan (ages 22-85) made a series of choices between a positively skewed risky gamble and either a certain outcome (Study 1) or risky symmetric gamble (Study 2). Logistic regression analyses revealed that people were more likely to choose moderately- and strongly skewed gambles over certain outcomes, with the exception of when there were large potential losses (Study 1). However, a stronger skewness did not increase preference for positively skewed gambles over symmetric gambles, findings which also may depend on the valence of the expected outcome (Study 2). Taken together, these results suggest that there may be a greater preference for more strongly positively skewed gambles but it 1) is dependent on what other gamble is presented and 2) is most prevalent for positive expected values. Additionally, contrary to previous findings, we did not find strong evidence of an age-related increase in positive skew bias in either study. However, exploratory analyses revealed that decision making strategy and cognitive abilities may play a role.

Keywords: decision making, risk taking, skew, strategy

Word count:

Boundary Conditions for the Positive Skew Bias

According to traditional theories of decision making under risk, when making risky decisions, people consider the expected value of each option before making a choice (Expected Utility Theory; von Neumann & Morgenstern, 1944, Mean-Variance Models; Markowitz, 1952). The expected value is determined by both the value or worth of the potential outcomes (i.e., expected utility) and the probability of each outcome occurring (i.e., risk). Yet, there is substantial evidence that the skewness, or asymmetry, in the probabilities of potential outcomes also plays an important role in the choices people make (Alderfer & Bierman, 1970; Kraus & Litzenberger, 1976; Menezes, Geiss & Tressler, 1980; Coombs & Lehner, 1981; Weber et al., 1994; Wu, Bossaerts, & Knutson, 2011). As such, theorists across the fields of economics, psychology and neuroscience have attempted to account for skewness within existing models and theories of decision making (e.g., Rank-Dependent Utility Theory; Quiggin, 1982, Cumulative Prospect Theory; Tversky & Kahneman, 1992), and more recently, skewness has been directly incorporated into newer theories of decision making (e.g., Dispersion and Skew Theory; Bayrak & Hey, 2020, Anticipatory Affect Theory; Knutson & Greer, 2008; Wu et al., 2011). Taking skewness into consideration is highly relevant because many of the important financial and medical decisions that people make involve skewed risky gambles where a large but unlikely outcome is coupled with a small but more likely outcome. However, relatively little is known about the boundary conditions for when individuals are most drawn to certain types of skewed gambles and the mechanisms that may explain this preference. Across two studies, we investigate the contexts in which individuals are most likely to prefer skewed gambles.

Skewed risky gambles can either be negatively or positively skewed. In negatively skewed gambles, there is a large but unlikely loss coupled with a small but likely gain, such as undergoing a minor medical procedure. While there is a small chance of permanent disability or even death resulting from complications, there is a much larger chance that the patient will see a small improvement in health. In contrast, in positively skewed gambles, there is a large but unlikely gain coupled with a small but likely loss, such as purchasing a lottery or raffle ticket. While there is a small chance of winning the large jackpot or prize, there is a much larger chance of losing the cost of the ticket. There is substantial evidence from both the laboratory and real-world risk tasking behavior that people tend to like these positive-skewed gambles, compared to gambles that are negatively skewed (Åstebro, Mata, & Santos-Pinto, 2015; Kraus & Litzenberger, 1976; cf. Symmonds et al., 2011), and to a lesser degree, those that are symmetrical (Burke & Tobler, 2011; Seaman et al., 2017). While one study found that preference for positive skewness is related to positive arousal (Wu, Bossaerts, & Knutson, 2011), it is not well understood what other factors may contribute to this positive skew bias. In the present work, we sought a better understanding of the conditions under which people are most likely to demonstrate a positive-skew bias by varying the degree of skewedness and the foil (i.e., alternative choice), and testing how these effects may be related to age and other individual difference measures. Identifying boundary conditions of the preference for positively skewed gambles will further elucidate why such a bias may occur and point to the mental processes that underly this preference.

From the animal literature, it appears that positive skew preference is not specific to humans, with both birds and monkeys also demonstrating a positive skew bias (Caraco & Chasin, 1984; Strait & Hayden, 2013; Genest, Stauffer, & Schultz. 2016). Furthermore, in rhesus monkeys, skew preference was found to depend on the degree of skew with both positive and negative strongly skewed gambles being selected more often than the weakly-skewed gambles.

To our knowledge, the degree of skewness not been systematically varied and compared in human work. Therefore, in this study, we varied the degree of skewness in risky decisions. We predicted that similar to the rhesus monkeys, people would also demonstrate a preference for the most strongly skewed gambles.

Because of considerable evidence that individuals tend to make different decisions under conditions of risk compared to certainty, we also tested whether the extent of the positive-skew bias may depend on the foil, or alternative choice, that was presented. In Study 1, participants had to decide between a positively skewed risky gamble and a certain (i.e., no gamble) option. In Study 2, people chose between two risky gambles—one positively-skewed and the other symmetric. By including two risky gambles in Study 2, this allowed us to separate skew preference from simple risk aversion and risk seeking. We predicted that the positive-skew bias would increase with greater skewness in both certain (Study 1) and risky (Study 2) foil conditions.

Additionally, recent work has found that the tendency to prefer positively skewed gambles becomes more exacerbated with age. That is, older adults are more likely to show a positive-skew bias than adults under the age of 65 (Seaman et al. 2017; Seaman et al., 2018). Because almost 25% of fraudulent schemes targeting the older adult population in the United States are framed in a positive-skew manner (Federal Bureau of Investigation, 2022), this may be contributing to the increased susceptibility to financial scam and fraud seen in later life. However, in the studies that previously documented age-related differences in positive-skew preference, only one level of skewness was tested. Therefore, to better understand age-related differences and the role of varied levels of skewness, in this study, we used a lifespan sample to determine the extent to which age and degree of skew may contribute to positive-skew bias. We predicted that the age-related difference in positive-skew bias may become even more pronounced under higher degrees of skewness.

Furthermore, in a series of exploratory analyses, we tested whether positive-skew bias was associated with several individual difference measures including (1) self-reported decision strategies, (2) typical affect, (3) cognitive abilities, and (4) real-world investment and fraud decisions. This will provide additional details about what other factors may contribute to a stronger positive skew bias.

In sum, across two studies, we investigated the conditions under which individuals are most drawn to positively-skewed gambles—that is, show the strongest positive-skew bias. We examined how various levels of skewness and the foils used influence the positive-skew bias and how this may differ across adulthood and with individual differences in strategies, typical affect, abilities, and experiences.

Experiment 1: Skewed Risky Gambles vs. Certain Outcomes

Method

Participants

Two hundred and nine participants (M_{age} = 53.64, SD_{age} = 17.16, Range = 22–85; 50.24% women; 79.9% White/Caucasian, 7.2% African American/Black, 5.7% Asian, 3.3% Hispanic/Latino, and <2% Pacific Islander, American Indian/Alaska Native, multiracial, or other) completed an online study using Qualtrics Panels. Participant sample size was determined a priori (N > 200) based on previous findings of small to moderate effect size in age-related differences in positive skew bias. Age and gender quotas were used to ensure the sample included equal numbers of men and women in each age decade. Participants were excluded if 1) they had a history of psychiatric/neurological illness or head injury 2) they answered either catch trial (where one option was substantially better) incorrectly. Participants who failed to meet the eligibility inclusion criteria were automatically removed by Qualtrics.

After completing a brief demographic survey, participants viewed instructions for the Skewed Gambling Task, answered three practice questions, then completed the task, described below. After completing the Skewed Gambling Task, participants completed a series of questionnaires about the strategies implemented during the task, their typical affect, their cognitive abilities, and personal experiences with bad investments and fraud. The Duke University Institutional Review Board approved all experimental procedures and the study was preregistered on OSF and can be found at https://osf.io/vwhxb

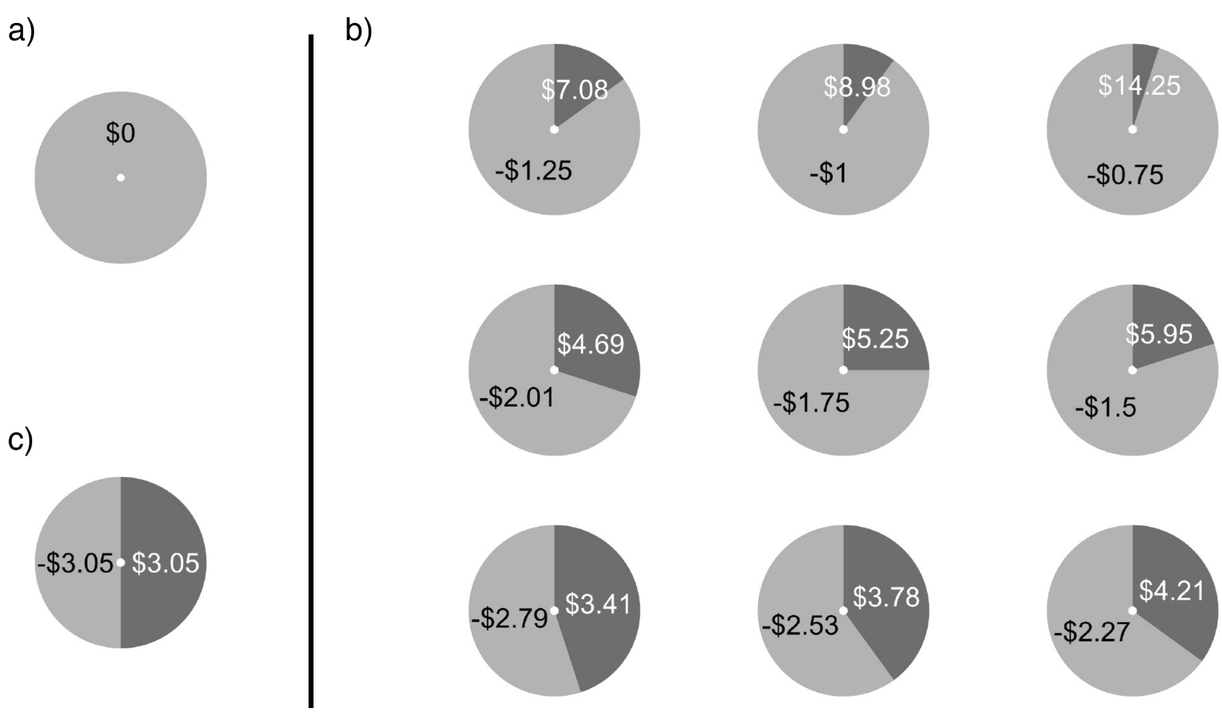
Measures

Skewed Gambling Task

During the skewed gambling task, participants saw a pair of gambles and were asked to choose between a certain outcome (Figure 1a) or a skewed risky gamble (Figure 1b). Each pair of gambles was displayed side by side with the probability of winning and losing presented as a pie chart with the win/loss amounts in U.S. dollars ($) next to the corresponding probability. On each trial, participants were prompted "which gamble would you like to choose?" and gamble choice was recorded. Participants were randomly assigned to one of five expected value (EV) conditions (EV = –$5, –$0.5, $0, +$0.5, or +$5), which was matched between the two choices in each pair. The risky gambles varied systematically in the degree of positive skewness on each trial, spanning from maximum uncertainty (50/50 gamble) to certainty (100% win) in 5% increments (variance = 500, skewness = 0 to ±46169). This led to a total of nine positively skewed gambles (three weakly-skewed (Figure 1b top row), three moderately-skewed (Figure 1b middle row), three strongly-skewed (Figure 1b bottom row)) and one symmetrical gamble (Figure 1c) for each

EV condition. A detailed spreadsheet of stimuli values can be found on OSF (https://osf.io/d56b2/)[1]. Each participant completed the ten choice trials that corresponded to their EV condition and two catch trials presented in a randomized order. Choices were hypothetical and participants received no feedback about the outcome of each gamble. Thus, the task was not incentive compatible, and participants were not paid according to their choices. This decision was informed by prior work that used similar tasks in online participant samples and found that skew bias exists regardless of whether the outcomes were real or not (Seaman et al., 2017; 2018).

Figure 1. Ten gambles presented in Study 1 Skewed Gambling Task for EV condition = $0. Participants chose between a certain outcome (a) and each of the nine matched-EV skewed gambles (b) and the symmetric gamble (c). Catch trials are not pictured.



[1] While the preregistration and stimuli data file also include negatively skewed gamble trials, pilot testing revealed the rate of attrition and number of random responses were too high when present. Thus, we decided to eliminate the negatively skewed gambles and compared positively skewed gambles to the symmetrical gambles, which has been done in previous work (see Burke & Tobler, 2011; Seaman et al., 2017)

Individual Difference Measures[2]

Self-Reported Strategy Use. We designed a questionnaire to probe self-reported decision strategies that participants may have used while making their decisions. The first two statements were taken from Figner and colleagues (2009) to determine the extent to which the overall strategies used by participants were affect-based ("I solved the task on a gut level") or deliberative-based ("I tried to solve the task mathematically"). The final four questions asked about the information participants used when trying to complete the task including win amount, loss amount, win probability, and loss probability (i.e., "I solved the task by focusing on how much money I could win/how much money I could lose/how likely it was that I would win/how likely it was that I would lose"). Participants responded to each of the six statements using a 5-point Likert scale ranging from *Strongly Disagree* (1) to *Strongly Agree* (5).

Typical Affect. Using the Affect Valuation Index (AVI; Tsai, Knutson, & Fung, 2006), participants reported how often they typically experience various emotions. Participants read 30 words describing feeling states and rated how much they actually feel each of them over the course of a typical week, ranging from *never* (1) to *all the time* (5). During data analysis, we discovered that the last six items were not shown to our participants including three positive state affect words (content, happy, satisfied), two negative state affect words (sad, unhappy), and one low arousal positive state word (serene). We were still able to calculate a score for low arousal positive states by averaging responses from the three other items related to that dimension (calm, relaxed, peaceful). We were also able to calculate a score for high arousal negative emotions by averaging responses from the three corresponding items (fearful, hostile, nervous). However,

[2] The preregistration states that we included the Future Time Perspectives Scale and Emotion Regulation Questionnaire. However, these were removed after piloting and before data collection to reduce the time and burden on participants.

because of the missing values, we were unable to estimate overall positive and negative affective scores.

Cognitive Abilities. We assessed participants on two relevant tests of cognitive abilities that may influence their risky decision-making of gambles: numeracy and graph literacy. Numeracy refers to the ability to understand numerical information. We measured numeracy using the 15-item DR Numeracy Test from Peters and colleagues (2007) where scores reflect the number of items (0 to 15) that were correct, with higher scores reflecting better numeracy. Graph literacy refers how well an individual can read and interpret information from graphs. Graph literacy was measured using the 10-item Subjective Graph Literacy Scale (Garcia-Retamero et al., 2016) where participants report how good they are at working with graphs on a scale from *not at all good* (1) to *extremely good* (6) with two reverse-coded items that asked about frequency and ease of use. Scores range from 10 to 60 such that a higher score indicates better self-reported graph literacy.

Real-World Investment and Fraud Decisions. We asked participants a series of questions about their experience with monetary investments and fraud. For investments, we asked participants if they ever made an investment where they lost some, or all, of the money they invested. If they reported they had, they also reported how many times, how much money they lost, how recent it was, and selected the reason they believed it occurred (e.g., bad investment, market downturn, uninformed, misled/defrauded). If they believed they were defrauded, they were asked if they reported the incident and why/why not. For fraud, participants were asked to report their ability to detect fraudulent investments and resist high-pressure sales tactics when buying investments. They also reported how likely they were to make a fraudulent investment, and to estimate how many potential fraudulent investments they have avoided.

Data Analysis

We used R (Version 3.6.1; R Core Team, 2019) for all analyses; data and code are available on OSF (https://osf.io/d56b2/). Hierarchical binary logistic regression models (formulas for each model can be found in the supplemental materials) were used to examine the effect of degree of skewness on gamble choice, carried out using the lme4 package in R Studio. In the baseline model, we test whether skewness (weak skew, moderate skew, strong skew, compared to symmetric/no skew; varied within-subjects) is a significant predictor of skewed gamble preference. In Model 1, we add the valence of the expected value (EV) (positive EV (EV = +$0.5, EV = +$5), negative EV (EV = –$0.5, EV = –$5), compared to neutral (EV = $0); varied between-subjects) and a valence by skewness interaction (weak skew/positive EV, moderate skew/positive EV, strong skew/positive EV, weak skew/negative EV, moderate skew/negative EV, strong skew/ negative EV, compared to symmetric/neutral) as predictors. In Model 2, we add the magnitude of the expected value (small (EV = –$0.5 and EV = +$0.5), large (EV = –$5 and EV = +$5), compared to none (EV = $0); varied between-subjects), and the interaction between skewness and magnitude (weak skew/small EV, moderate skew/small EV, strong skew/small EV, weak skew/large EV, moderate skew/large EV, and strong skew/large EV, compared to symmetric/none(EV = 0) as predictors. Because valence and magnitude were not completely orthogonal in this design, in Model 3, we include two additional predictors: 1) an interaction factor that includes both magnitude and valence (negative/large (EV = –$5), negative/small (EV = –$0.5), positive/small (EV = +$0.5) , positive /large (EV = +$5), compared to neutral/none (EV = $0)) and 2) the interactions between skewness and the magnitude/valence interaction term (weak skew/EV = –$5, moderate skew/EV = –$5, strong skew/EV = –$5, weak skew/EV = –$0.5, moderate skew/EV = –$0.5, strong skew/EV = –$0.5, weak Skew/EV = +$0.5, moderate skew/EV = +\$0.5, strong skew/EV = +\$0.5, weak skew/EV = +\$5, moderate skew/EV = +\$5, strong skew/EV = +\$5, compared to symmetric/EV = \$0). In Model 4, we add age (varied between-subjects, continuous variable) as a predictor. Equations for each model can be found in the supplemental materials.

To determine how individual difference measures influenced the preference for positively skewed gambles, we calculated a positive skew bias score for each participant by adding up the number of times they chose a skewed gamble. This measure ranged from 0 (no bias—no positive skewed gambles were selected) to 9 (strong bias—all positively skewed gambles were selected). We then used correlational analyses to test whether an individual's strategies, typical affect, numeracy, subjective graph literacy, and real-world investment and fraud experiences were related to their demonstrated positive-skew bias.

Results

Skewed Gamble Preference

Relative to the certain outcome, participants selected symmetric gambles 55% of the time (45% certain outcome) and positively skewed gambles 62% of the time (weak skew = 54%, moderate skew = 65%, strong skew = 70; 38% certain outcome), indicating an overall positive-skew bias in this sample. As predicted, there was a main effect of degree of skewness (Table 1, Baseline Model), such that there was a larger preference for moderately- and strongly-skewed gambles relative to symmetric gambles (moderately-skewed: $t(208) = -2.95$, $p = 0.004$; strongly-skewed: $t(208) = -4.19$, $p < .001$). Weakly-skewed gambles were not chosen at a different rate than symmetric gambles ($p > .05$).

Next, we tested if the valence of the expected value (EV) moderated this effect by adding valence and its interaction with skewness to the baseline model as predictors (Table 1, Model 1).

Adding these predictors significantly improved model fit, χ^2 (8, N = 209) = 29.23, p < .001. While the pattern previously identified persisted for the positive EV conditions, people were *not* more likely to select moderately- and strongly-skewed gambles with negative EVs (moderately-skewed: t(81) = -0.82, p = 0.413, strongly-skewed: t(81) = -0.89, p = 0.377.

We then tested if magnitude of the EV moderated the effect of degree of skew by adding magnitude and its interactions to the baseline model (Table 1, Model 2). Adding these predictors also significantly improved model fit, χ^2 (8, N = 209) = 24.60, p = 0.002. People were *not* more likely to choose moderately- and strongly-skewed gambles with large magnitudes (EV = +5 or –5; (moderately skewed: t(82) = 1.03, p = 0.305, strongly skewed: t(82) = -0.39, p = 0.698).

Because valence and magnitude were not completely orthogonal in this design, we also tested an interaction factor that included both magnitude and valence and added this to the baseline model (Table 1, Model 3). Adding this predictor significantly improved model fit, χ^2 (16, N = 209) = 54.66, p < .001. In contrast to the other conditions where people tended to prefer the more heavily skewed options (EV = –0.5, 0, and +0.5) people did not demonstrate this pattern in the large negative EV condition (EV = –5; moderately-skewed: t(37) = 1.31, p = 0.198, strongly-skewed: t(37) = 1.90, p = 0.065; see Figure 2). Additionally, in the large positive EV condition (EV = +5), there was only a nonsignificant trend towards being more likely to choose strongly-skewed gambles over symmetric gambles (t(44) = -1.91, p = 0.063) and people were not more likely to select moderately-skewed gambles over symmetric gambles (t(44) = 0.26, p = 0.793). Thus, consistent with our first hypothesis, there was a pattern of increased preference for gambles with greater skewness but this effect depends on both the valence and magnitude of the expected values such that people do not appear to prefer skewed gambles with large potential losses, and may demonstrate a different pattern for large potential gains.

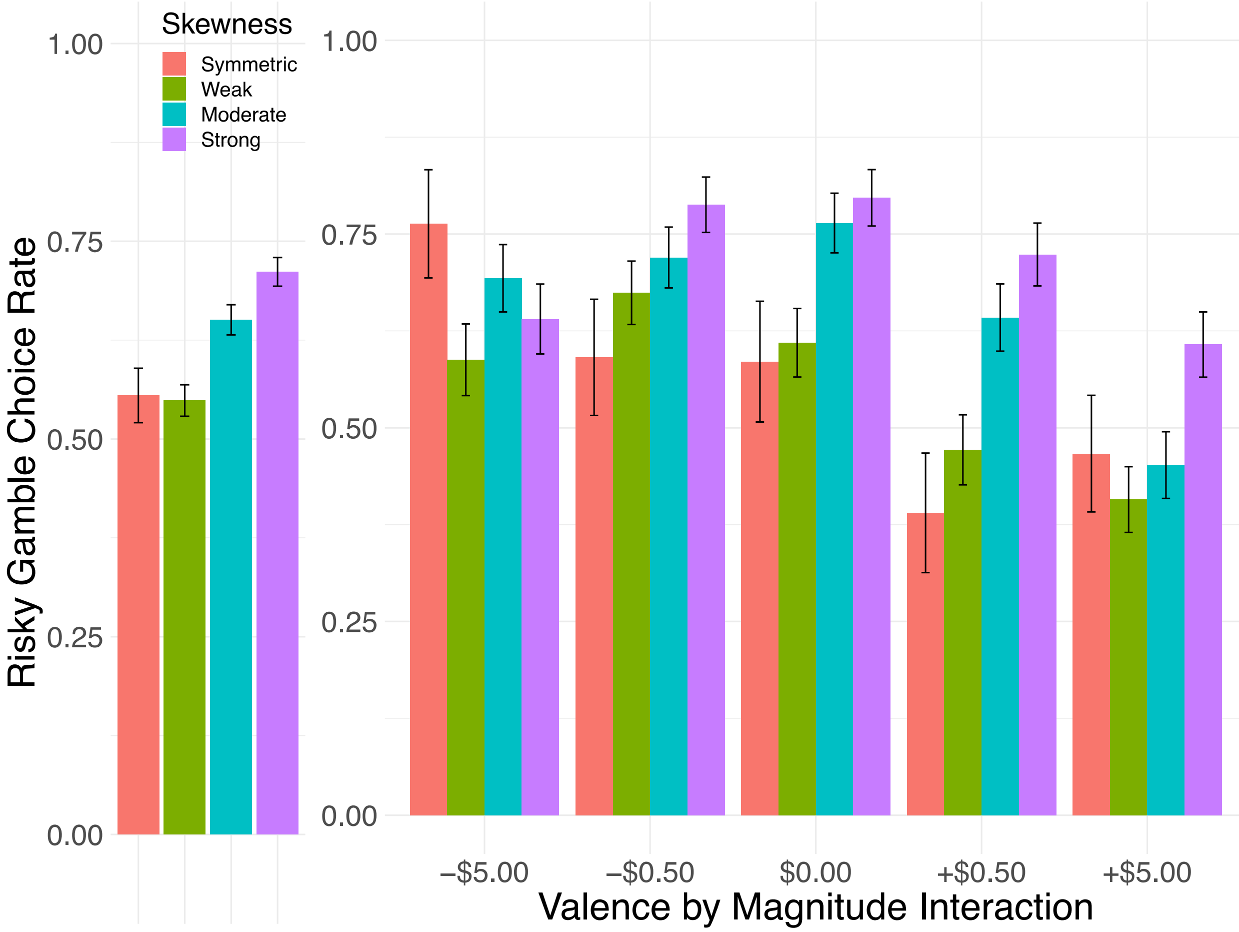


Figure 2. Results from Study 1, Baseline Model (left) and Model 3 (right).

Finally, we tested whether there was a difference in skewed gamble choice across the adult lifespan by adding age a predictor to the model (Table 1, Model 4). Contrary to our second prediction, adding age did not improve model fit, χ^2 (1, N = 209) = 0.01, p = 0.928, and did not predict gamble choice. To better understand this unexpected null effect, we ran a series of exploratory analyses (see supplemental materials for models and results). However, none of the additional analyses yielded significant age effects. Because age was not a significant predictor of gamble choice, we do not examine age effects in our individual difference analyses below. However, a correlation matrix with the relationships between all individual difference measures, including age, can be found in supplemental Table S3.

Individual Difference Exploratory Analyses

Self-Reported Strategy Use

Participants reported using an affective strategy more than a deliberative strategy ($t(208) = 2.39$, $p = 0.02$) and stronger endorsement of an affective strategy was related to a greater preference for positively-skewed gambles, $r = 0.17$, $p = 0.012$. There was no relationship between endorsement of a deliberative strategy and skewed gamble choice ($p > .05$). Additionally, participants reported their strategies focused more on wins, compared to losses, $F(1, 831) = 28.95$, $p < .001$. People who endorsed strategies that focused on losses were more likely to reject positively skewed gambles. This was true for both monetary loss ($r = -0.40$, $p < .001$) and the likelihood of loss ($r = -0.34$, $p < .001$). Furthermore, people who endorsed strategies that focused on how much money they could win were more likely to select the skewed gambles, $r = 0.35$, $p < .001$. All these relationships remained the same size and direction when controlling for the expected value condition participants were randomly assigned (see supplementary materials).

Typical Affect

Participants reported experiencing low arousal - positive emotions (e.g. calm, relaxed, or peaceful; $M = 3.46$) the most and experiencing high arousal - negative emotions (e.g. fearful, hostile, or nervous; $M = 1.84$) the least. However, there was no relationship between typical affect and skewed gamble choice (all ps $> .05$).

Cognitive Abilities

Better numeracy and subjective graph literacy were both associated with decreased preference for positively skewed gambles (numeracy: $r = -0.20$, $p = 0.003$; subjective graph literacy: $r = -0.20$, $p = 0.004$). Both these relationships remained the same size and direction when controlling for the expected value condition participants were randomly assigned (see supplemental materials).

Real-World Investment and Fraud Decisions

While we found no relationship between reports of losing money through risky investments or fraud and the positive-skew bias, there was a significant relationship between people's confidence in their ability to resist high-pressure sales tactics and the likelihood to select positively skewed gambles such that people who were more confident were less likely to exhibit the positive-skew bias, $r = -0.16$, $p = 0.024$. This relationship remained the same size and direction when controlling for the expected value condition of participants (see supplemental materials).

Study 1 Interim Discussion

Consistent with our initial prediction, we found that moderately and strongly skewed gambles were selected more than weakly-skewed and symmetric gambles, indicating a stronger preference for skewed gambles as the degree of skewness increases. However, this effect appears to depend on both valence and magnitude of the expected values and was most prevalent for small positive EV (EV = +$0.5), small negative EV (EV = –$0.5), and neutral outcomes (EV = $0). Our findings suggest that people may demonstrate a different skew preference pattern for large positive EV outcomes (i.e., large gains) and may not prefer skewed gambles at all for large negative EV outcomes (i.e., large losses). Surprisingly, we did not find an age-related increase in preference for positively skewed gambles. This is contrary not only to our hypotheses but is also inconsistent with prior studies of age differences in skewed gamble preference, and thus merits further exploration. Collectively, our exploratory analyses on individual difference measures suggest that using strategies that are more affective, and those that focus on winning, are associated with greater positive-skew bias, whereas strategies that focus on possible losses are related to less positive-skew bias. Furthermore, those who had higher numeracy, subjective graph literacy, and were more confident in their ability to avoid fraudulent investments were less likely to select positively skewed gambles. These findings indicate that affective mechanisms may fuel positively skewed gamble preference while cognitive mechanisms may fuel positively skewed gamble avoidance.

One problem with the outcome measure in this study, positive-skew bias, is that the extreme ends of this measure cannot be disentangled from risk-aversion and risk-seeking. In other words, if someone always chose the certain outcome (positive-skew bias = 0), it could be because they were avoiding positively skewed gambles or it could be because they were generally risk-averse. Likewise, if someone always chose the uncertain gamble (positive-skew bias = 9), it could be because they strongly prefer positively skewed gambles or it could be because they are generally risk-seeking. To avoid this confound, in Study 2 we altered the Skewed Gambling Task such that participants were forced to make a choice between two risky gambles—a skewed gamble and a symmetric (i.e., not skewed) gamble.

Experiment 2: Skewed vs. Symmetric Risky Gambles

Method

Participants

Two hundred and ten participants (M_{age} = 54.53, SD_{age} = 16.95, Range = 25 – 85; 51.4% women; 77.1% White, 7.1% African African/Black, 10% Asian, 2.4% Hispanic/Latino, and <3% Pacific Islander, American Indian/Alaska Native, multiracial, or other) were recruited using Qualtrics Panels; the survey file is available on OSF (https://osf.io/d56b2/). The sample size (N > 200) was determined a priori and was intended to match that of Study 1. The same quotas and exclusion criteria from Study 1 were used and those who failed to meet the inclusion criteria were automatically removed by Qualtrics. In Study 2, a variant of the skewed gambling task was used, as described below. All other procedures and measures remained the same as in Study 1. Study 2 was also preregistered on OSF and can be found at https://osf.io/vwhxb.

Skewed Gambling Task

In this variant of the skewed gambling task, participants saw a pair of two risky gambles and chose between either a symmetric (Figure 1c) or a skewed (Figure 1b) gamble. As in Study 1, pairs of gambles were presented side by side with the probability of winning and losing presented as a pie chart with the win/loss amounts in U.S. dollars ($) next to the corresponding probability. On each trial, participants were prompted with "which gamble would you like to choose?" and gamble choice was recorded. Participants were randomly assigned to one of five expected value (EV) conditions (EV = –$5, –$0.5, $0, +$0.5, or +$5) with the skewed gambles varying systematically in the degree of positive skewness, spanning from maximum uncertainty (50/50 gamble) to certainty (100% win) in 5% increments (variance = 500, skewness = 0 to ±46169). Thus, each participant completed nine trials where they chose between positively skewed gambles (three weakly-skewed, three moderately-skewed, three strongly skewed) and the corresponding symmetrical gambles with matched EV. Each participant completed the nine choice trials that corresponded to their EV condition and two catch trials presented in a random order. As in Study 1, choices were hypothetical, gambles did not play out, and participants received no feedback about their choices.

Data Analysis

The same analysis plan used in Study 1 was used in Study 2 except for instead of having four levels for skewedness (symmetric, weak skew, moderate skew, strong skew), there are only three (weak skew, moderate skew, strong skew). In a series of hierarchical binary logistic regressions (formulas for each model can be found in the supplemental materials) conducted in R studio, the baseline model tests whether degree of skewness (weak skew, moderate skew, strong skew; varied within-subjects) is a significant predictor of skewed gamble preference. In Model 1, we add the valence of the expected value (EV) (positive EV(EV = +0.5, EV = +5), negative EV (EV = –0.5, EV = –5), compared to neutral (EV = 0); varied between-subjects) and a valence by skewness interaction (moderate skew/positive EV, strong skew/positive EV, moderate skew/negative EV, strong skew/negative EV, compared to weak skew/neutral) as predictors. In Model 2, we add the magnitude of the EV (small (EV = –0.5, EV = +0.5), large (EV = –5, EV = +5), compared to none (EV = 0); varied between-subjects), and interactions between skewness and magnitude (moderate skew/small EV, strong skew/small EV, moderate skew/large EV, strong skew/large EV, compared to weak skew/none (EV = 0). Similar to Study 1, in Model 3, we added a valence and magnitude interaction factor (negative/large (EV = –$5), negative/small (EV = –$0.5), positive/small (EV = +$0.5) , positive /large (EV = +$5), compared to neutral/none (EV = $0), and valence, magnitude and skewness interactions (moderate skew/EV = –$5, strong skew/EV = –$5, moderate skew/EV = –$0.5, strong skew/EV = –$0.5, moderate skew/EV = + $0.5, strong skew/EV = +$0.5, moderate skew/EV = +$5, strong skew/EV = +$5, compared to weak skew/EV = $0) as predictors. In Model 4, we add age (varied between-subjects, continuous variable) as a predictor.

Results

Skewed Gamble Preference

Participants chose the positive-skew gambles 74% of the time (weak skew = 76%, moderate-skew = 74%, strong-skew = 73%) and the symmetric risky gambles only 26% of the time, indicating a strong overall bias for positively skewed gamble.

While there was a main effect of degree of skewness (Table 2, Binary Logistic Regression Baseline Model), it was in the opposite direction of predictions and what was found in Study 1. There was a small but significant *decrease* in preference for moderately- and strongly-skewed gambles compared to weakly-skewed gambles (Figure 2; moderately-skewed: $t(209) = 2.12$, $p = 0.035$, strongly-skewed: $t(209) = 2.15$, $p = 0.033$).

We next tested if this relationship was modified by the valence of the expected value by adding valence and its interactions to the baseline model (Table 2, Model 1). Adding these predictors significantly improved model fit, χ^2 (6, $N = 210$) = 23.41, $p = 0.001$. In particular, people were less likely to choose strongly skewed gambles with negative EV outcomes ($t(83) = 3.58$, $p = 0.001$).

We also tested if magnitude of the expected value moderated the effect of degree of skew by adding magnitude and its interactions to the baseline model (Table 2, Model 2). Unlike the first study, adding these predictors did not significantly improve model fit, χ^2 (6, $N = 210$) = 10.07, $p = 0.122$.

As in Study 1, valence and magnitude of the expected values were not completely orthogonal. We again created a factor that included the magnitude and valence interaction and added this and its interaction with skewness to the baseline model (Table 2, Model 3). Adding this factor significant improved model fit, χ^2 (6, $N = 210$) = 14.88, $p = 0.021$. People only significantly chose strongly-skewed gambles less than weakly-skewed gambles for small, negative EVs (EV = –\$0.50, $t(41) = 2.88$, $p = 0.006$), which appears to be driving the finding that skewed gamble preference may decrease with increasing degrees of skewness (see Figure 3).

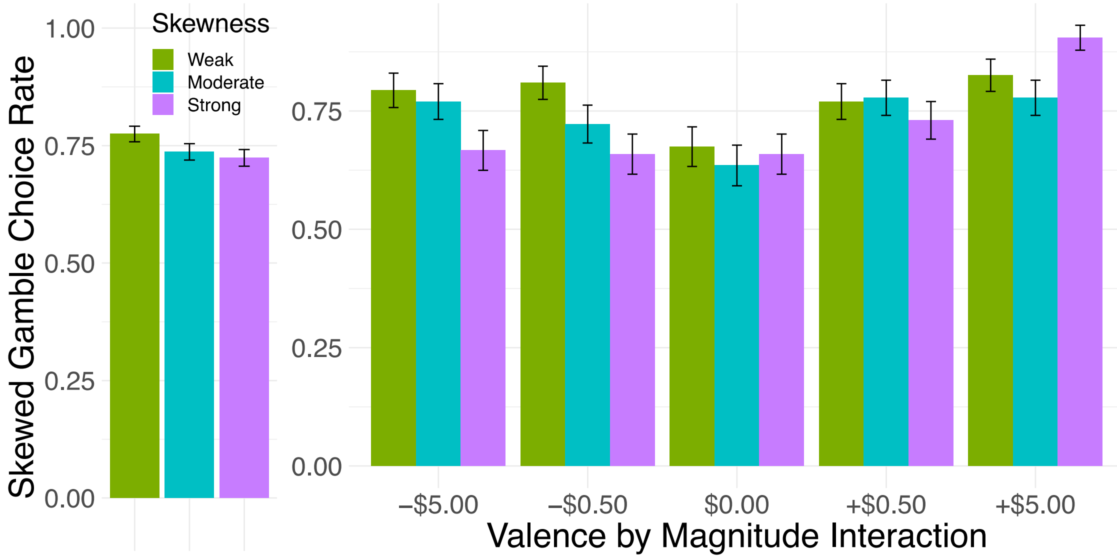


Figure 3. Results from Study 2, Baseline Model (left) and Model 3 (right).

Finally, we tested whether there was a difference in gamble choice across the adult lifespan. In Model 4 we added age as a predictor to the model (Table 2, Model 4). Contrary to our prediction, adding age did not improve model fit, χ^2 (1, $N = 210$) = 1.48, $p = 0.224$, and age did not predict gamble choice. Exploratory analyses on age and gamble choice did reveal a small but significant effect of age (Odds Ratio = 1.82, p = .022), but only for one of the three models tested (See supplemental materials for the models and results). Like Study 1, we do not examine age effects in our individual difference analyses below. However, Table S3 is a correlation matrix displaying the relationships between all the individual measures, including age, that appears in the supplemental material.

Individual Difference Exploratory Analyses

Self-Reported Strategy Use

Contrary to Study 1, participants in this study reported using a deliberative strategy more than an affective strategy ($t(209) = -3.90$, $p < .001$) and neither strategy type was related to skewed gamble preference (rs > 0.12). In terms of information, similar to findings in Study 1, people reported their strategies focused more on wins instead of losses ($F(1, 831) = 4.50$, $p < .001$) and those who focused more on how much they could win were more likely to choose skewed gambles ($r = 0.27$, $p < .001$). This effect remained when controlling for the expected value condition participants were randomly assigned (see supplemental materials). While those who focused more on the likelihood of losing were less likely to choose skewed gambles initially ($r = -0.14$, $p = 0.050$), this effect did not survive when controlling for expected value condition.

Typical Affect

Similar to Study 1, participants reported experiencing low arousal–positive emotions (e.g. calm, relaxed, or peaceful; $M = 3.47$) the most and experiencing high arousal–negative emotions (e.g. fearful, hostile, or nervous; $M = 2.31$) the least. Unlike in Study 1, some of these emotions were related to skewed decision making. In particular, people who endorsed high arousal (e.g. aroused, surprised, or astonished; $r = 0.13$, $p = 0.051$) and high arousal - positive (e.g. enthusiastic, excited, strong, or elated; $r = 0.17$, $p = 0.013$) words over the course of a typical week were more likely to choose the skewed gambles.

Cognitive Abilities

Better numeracy initially predicted avoidance of positively skewed gambles ($r = -0.14$, $p = 0.035$) but this result did not survive when controlling for the participant's expected value condition. Subjective graph literacy was not associated with skewed gamble preference in this sample ($r = -0.11$, $p = 0.109$).

Real-World Investment and Fraud Decisions

None of the real-world decisions we measured were related to the preference for positively skewed gambles (all *p*s > .05).

Study 2 Interim Discussion

Overall, we find a strong positive skew bias, with participants choosing positively skewed gambles more often than symmetric gambles. Yet, contrary to our predictions, when choosing between two risky outcomes (positively skewed vs. symmetric), positively skewed gamble preference did not increase with larger degrees of skew. In fact, choosing the strongest positively-skewed gambles may even decrease in certain cases—such as those with negative expected values. Once again, we did not find clear evidence of an age-related increase in preference for positively skewed gambles. Based on the exploratory analyses on individual differences, it appears that, just as in Study 1, using strategies that focus on the possible winnings may be related to a larger positive-skew bias. After controlling for expected value condition, no significant relationships were identified between positive skew gamble preference and numeracy, graph literacy, or real-world decisions.

General Discussion

These two studies examined the conditions under which the positive-skew bias is most strongly present. Across both studies and foils, we see an overall preference for positive-skewed, relative to symmetric, gambles. In line with our hypothesis, in Study 1, we found that when choosing between a certain and risky gamble, the positive-skew bias increased with larger degrees of skewness. However, in Study 2, we found that when choosing between two risky gambles, positive-skew bias did not increase under more strongly skewed conditions. Both effects appear to be dependent on the valence and magnitude of the expected values.

Surprisingly, we found inconsistent evidence of age-related differences in positive-skew bias. However, some of our exploratory analyses indicate that certain strategies and abilities may play a role in positive skew preference.

Our initial hypothesis that preference for positive skew would depend on the degree of skewness was based on a primate study which found that monkeys demonstrated a stronger preference for stronger positively skewed gambles (Strait and Hayden, 2013). However, in this work, monkeys were only making decisions about positive expected values. Here we asked people to make decisions for positive, negative, and neutral expected values and we found some evidence across both our studies of a reflection or sign effect—that is, where choices may diverge between gambles with positive vs. negative expected values (Fagley, 1993)—and that these effects may be exacerbated by the magnitude of the potential gains or losses. For instance, in Study 1, the preference for more strongly skewed gambles was seen across conditions with the exception of large negative expected values (EV = –$5). In Study 2, the unexpected pattern of skewed gamble avoidance for more strongly-skewed gambles only occurred with negative EVs (EV = –$5 and –$0.50). Under neutral and positive EV conditions, there were no differences in gamble preference between degree of skew, and for the highest positive EV condition (EV = +$5), the pattern appeared similar to that of Study 1 where the most strongly skewed gambles were preferred. Therefore, it appears as though several features of the gambles matter for positive skew bias including the foil, the degree of skewness, and the valence and magnitude of the expected outcomes. These effects should be further explored in future studies using a within-subject design for even more direct comparisons.

We found inconsistent age effects in preference for positively skewed gambles. In Study 1, age was not a significant predictor of gamble choice for any of the models tested. In Study 2, there was only a small effect of age on skewed gamble choice and this was only significant in one of the four total models tested. Therefore, there was not strong evidence across these studies that age influenced skew bias. This contrasts prior studies that have found age-related increases in positive skew bias (Seaman et al., 2017; 2018). Even after limiting our sample to those who completed trials most similar to the previous work (Study 1, EV = \$0, $N = 41$), we saw no effects of age[3]. There are several possible reasons we did not see a robust effect here. First, these studies differ from prior studies in several notable ways. For instance, in previous studies, a limited set of conditions was used (expected value = \$0, skewness = 1.25). Here, we varied both expected value and skewness. It is possible that age differences only appear under very specific conditions. Second, in the previous work, individuals also considered negatively skewed gambles with the age effects being strongest when contrasting between negatively and positively skewed gambles (Seaman et al., 2017). Since symmetric gambles, rather than negatively skewed gambles, were used for comparison in the current studies, smaller changes in gamble preference may have been undetectable. Finally, it is possible that the age-related positive-skew bias observed in prior studies was a statistical abnormality. Thus, further studies are needed to determine the existence of this phenomenon and how robust it is to different gamble characteristics and conditions.

Many dual process models decision making suggest that risk taking is a result of competition between a more reactive affective system and a more controlled deliberative system (Figner et al., 2009). Prior studies of skewed gambling in young adults have shown greater affective response to positively skewed gambles (Wu et al., 2011), suggesting that affective processes may lead to a preference for positively-skew gambles. We found support for this perspective in Study 1, where participants were more likely to endorse an affective (compared to

[3]This subsample skews older than the whole study sample with the mean age = 57 years old and the majority of the sample being aged ≥ 60.

deliberative) strategy and individuals using an affective strategy were more likely to choose positively skewed gambles. However, neither of these trends were present in Study 2; in fact, participants in Study 2 were more likely to endorse a deliberative (compared to affective) strategy. It is possible that the samples for each study differed in terms of their preferred strategy, or it is possible that the type of questions encountered in each study influenced the type of strategy pursued by participant. A difference in strategy that is dependent on the foil may partially explain why the results were not fully consistent between studies. Perhaps individuals were more likely to rely on their gut (affective) in the certain vs. risky condition because the cognitive costs were relatively low while individuals were more likely to rely on deliberation when facing two risky gambles. While affective strategies were not predictive of positive skew bias in Study 2, emotions reported being typically experienced by participants was predictive of skew bias. Individuals who reported experiencing more high arousal or high arousal-positive emotions during the course of a typical week were more likely to choose positively skewed gambles. Collectively, across both studies, there is initial evidence that affective strategies and experiences may be associated with a bias towards positively skewed gambles.

Across both studies, participants who focused more on the monetary amounts of possible wins were more likely to choose positively skewed gambles. Here, because we equated the options on expected value, the potential winnings for skewed gambles were always larger than the alternative option. Research has also shown that greater visual attention to specific decision features can increase the likelihood that that option is chosen (Krajbich, Armel, & Rangel, 2010; Krajbich & Rangel, 2011). By focusing more on the monetary gains, it is possible that participants overweighted the possible gains and that led them to select more positively skewed gambles. Research has also shown that focusing on potential wins increases risk taking (Nygren, 1998). In Study 1, the skewed gamble was also the only risky option, so it is possible that focusing on possible wins caused participants to choose the skewed gamble more often. Future studies could examine visual attention during skewed decision making to determine if participants' subjective reports align with objective measures of visual attention.

Participants across both studies with better numeracy were more likely to *avoid* skewed gambles, although this effect was non-significant after controlling for expected value in Study 2. This is largely consistent with research showing that less numerate individuals are more susceptible to framing effects (Peters & Levin, 2008), take more disadvantageous risks (Jasper, Bhattacharya, Levin, Jones, & Bossard, 2013), and use simple strategies and affect when making decisions (Pachur & Galesic, 2013). Here, it is possible that individuals with stronger numeracy skills were more likely to engage in a deliberative strategy and avoid skewed gambles, while individuals with weaker numeracy skills were more likely to engage an affective strategy and choose the skewed gambles. Interventions aimed at improving risk communication using icon arrays instead of pie charts (as was presented here) could improve risk comprehension (Galesic, Garcia-Retamero, & Gigerenzer, 2009) and potentially mitigate the positive-skew bias in low numeracy individuals. While these individual differences findings are intriguing, follow-up studies designed to directly test these effects are needed to clarify the role of age, strategy, and ability in the preference for positively skewed gambles.

There are also several other limitations of this study. First, the expected value of the gamble varied between subjects; this means that differences we saw between valence (negative or positive expected values) and magnitude (+/–$5.00 or +/–$0.50) may be due to individual differences in those samples instead of based on the conditions. Similarly, the foil to skewed gambles (either an equivalent certain option or a symmetric risky gamble) varied between studies, so the difference in positively skewed gamble preference we observe between studies could also be due to sample characteristics. Future studies should vary these features within subjects to get a complete understanding of how gamble features (like expected value) or decision context (like foil) influence the preference for positively skewed gambles. Other things to consider are the lack of incentive-compatibility in the present study, as well as the stimuli presentation format (i.e., pie charts). Previous research on positive skew bias varies across these aspects, both of which might influence boundary conditions. Future work that directly compares these would be beneficial for better understanding how and when preference for positive skew gambles exist.

In conclusion, although the positive skew bias seems to grow stronger with increasing skewness, this seems to be limited to choices with positive expected values and is more prevalent when choosing between a certain and risky outcome. Additional work is needed to elucidate under what contexts and conditions that positive skew bias may change across the adult lifespan. Exploratory analyses reveal a general pattern of affective mechanisms possibly increasing the positive skew bias, but follow-up work is still needed. A better understanding of these underlying mechanisms can inform the development of specific interventions to reduce the positive-skew bias in everyday decision making.

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Table 1. Study 1 Hierarchical Logistic Regression Results.

	Baseline Model			**Model 1**			**Model 2**			**Model 3**			**Model 4**		
Predictors	Odds Ratios	CI	p	Odds Ratios	CI	p	Odds Ratios	CI	p	Odds Ratios	CI	p	Odds Ratios	CI	p
(Intercept)	1.59	0.94–2.70	.082	1.93	0.56–6.64	.298	1.93	0.56–6.67	.297	1.94	0.56–6.71	.297	1.93	0.55–6.71	.302
Skewness [Weak]	0.95	0.62–1.45	.809	1.22	0.45–3.34	.698	1.22	0.45–3.34	.698	1.22	0.45–3.35	.698	1.22	0.45–3.35	.698
Skewness [Moderate]	2.23	1.45–3.43	**<.001**	5.18	1.77–15.13	**.003**	5.19	1.77–15.17	**.003**	5.20	1.77–15.22	**.003**	5.19	1.77–15.21	**.003**
Skewness [Strong]	3.86	2.49–6.00	**<.001**	7.56	2.51–22.80	**<.001**	7.58	2.51–22.88	**<.001**	7.60	2.52–22.95	**<.001**	7.60	2.52–22.95	**<.001**
Valence [Positive EV]				0.29	0.06–1.30	.105									
Valence [Negative EV]				2.29	0.50–10.44	.285									
Skewness [Weak] * Valence [Positive EV]				0.88	0.25–3.03	.835									
Skewness [Moderate] * Valence [Positive EV]				0.51	0.14–1.85	.303									
Skewness [Strong] * Valence [Positive EV]				1.00	0.26–3.77	.998									
Skewness [Weak] * Valence [Negative EV]				0.61	0.18–2.09	.429									
Skewness [Moderate] * Valence [Negative EV]				0.26	0.07–0.96	**.044**									
Skewness [Strong] * Valence [Negative EV]				0.20	0.05–0.75	**.017**									
Magnitude [Small EV (0.5)]							0.54	0.12–2.40	.417						
Magnitude [Large EV (5)]							1.31	0.29–6.02	.727						
Skewness [Weak] * Magnitude [Small EV]							1.56	0.46–5.28	.477						
Skewness [Moderate] * Magnitude [Small EV]							0.86	0.24–3.10	.818						
Skewness [Strong] * Magnitude [Small EV]							1.14	0.31–4.28	.841						

Skewness [Weak] * Magnitude [Large EV]	0.31	0.09–1.07	.064						
Skewness [Moderate] * Magnitude [Large EV]	0.14	0.04–0.50	**.003**						
Skewness [Strong] * Magnitude [Large EV]	0.16	0.04–0.60	**.007**						
Magnitude/Valence [–5]				5.33	0.84–33.90	.076	5.37	0.84–34.36	.076
Magnitude/Valence [–0.5]				1.22	0.22–6.84	.821	1.23	0.22–6.91	.816
Magnitude/Valence [+0.5]				0.23	0.04–1.30	.097	0.23	0.04–1.31	.098
Magnitude/Valence [+5]				0.39	0.07–2.28	.299	0.40	0.07–2.31	.304
Skewness [Weak] * Magnitude/Valence [–5]				0.18	0.04–0.82	**.027**	0.18	0.04–0.82	**.027**
Skewness [Moderate] * Magnitude/Valence [–5]				0.10	0.02–0.48	**.004**	0.10	0.02–0.48	**.004**
Skewness [Strong] * Magnitude/Valence [–5]				0.04	0.01–0.22	**<.001**	0.04	0.01–0.22	**<.001**
Skewness [Weak] * Magnitude/Valence [–0.5]				1.61	0.40–6.56	.503	1.61	0.40–6.56	.503
Skewness [Moderate] * Magnitude/Valence [–0.5]				0.56	0.13–2.41	.438	0.56	0.13–2.41	.438
Skewness [Strong] * Magnitude/Valence [–0.5]				0.74	0.16–3.30	.690	0.74	0.16–3.30	.690
Skewness [Weak] * Magnitude/Valence [+0.5]				1.55	0.37–6.45	.544	1.55	0.37–6.45	.544
Skewness [Moderate] * Magnitude/Valence [+0.5]				1.36	0.31–6.05	.683	1.37	0.31–6.05	.682
Skewness [Strong] * Magnitude/Valence [+0.5]				1.85	0.40–8.54	.433	1.85	0.40–8.55	.432
Skewness [Weak] * Magnitude/Valence [+5]				0.45	0.11–1.97	.292	0.45	0.10–1.97	.292
Skewness [Moderate] * Magnitude/Valence				0.17	0.04–0.75	**.020**	0.17	0.04–0.75	**.020**

[+5]															
Skewness [Strong] * Magnitude/Valence [+5]										0.51	0.11–2.37	.391	0.51	0.11–2.37	.391
Age													1.02	0.68–1.54	.928

Random Effects

σ^2	3.29	3.29	3.29	3.29	3.29
τ_{00}	7.24 $_{ID}$	7.22 $_{ID}$	7.28 $_{ID}$	7.34 $_{ID}$	7.34 $_{ID}$
τ_{11}	0.00 $_{ID.Age}$				
ρ_{01}	1.00 $_{ID}$				
ICC		0.69	0.69	0.69	0.69
N	209 $_{ID}$	209 $_{ID}$	209 $_{ID}$	209 $_{ID}$	209 $_{ID}$
Observations	2090	2090	2090	2090	2090
Marginal R^2 / Conditional R^2	0.095 / NA	0.079 / 0.712	0.060 / 0.707	0.096 / 0.720	0.096 / 0.720

Table 2. Study 2 Hierarchical Logistic Regression Results.

	Baseline Model			Model 1			Model 2			Model 3			Model 4		
Predictors	Odds Ratios	CI	p	Odds Ratios	CI	p	Odds Ratios	CI	p	Odds Ratios	CI	p	Odds Ratios	CI	p
(Intercept)	13.87	7.78–24.70	**<.001**	5.55	1.82–16.90	**.003**	5.52	1.82–16.77	**.003**	5.63	1.82–17.37	**.003**	5.89	1.90–18.27	**.002**
Skewness [Moderate]	0.67	0.4 –0.96	**.029**	0.68	0.31–1.47	.324	0.68	0.31–1.47	.324	0.67	0.31–1.47	.323	0.68	0.31–1.47	.324
Skewness [Strong]	0.59	0.41–0.85	**.004**	0.85	0.39–1.86	.691	0.85	0.39–1.86	.691	0.85	0.39–1.86	.690	0.85	0.39–1.86	.691
Valence [Positive EV]				3.48	0.88–13.70	.075									
Valence [Negative EV]				3.20	0.82–12.47	.094									
Skewness[Moderate] * Valence [Positive EV]				1.19	0.45–3.14	.729									
Skewness[Strong] * Valence [Positive EV]				1.48	0.55–3.96	.435									
Skewness[Moderate] * Valence [Negative EV]				0.82	0.31–2.15	.680									
Skewness [Strong] * Valence [Negative EV]				0.30	0.11–0.78	**.014**									
Magnitude [Small EV(0.5)]							3.78	0.95–14.98	.058						
Magnitude [Large EV(5)]							3.01	0.78–11.57	.109						
Skewness [Moderate] * Magnitude [Small EV]							0.91	0.34–2.44	.844						
Skewness [Strong] * Magnitude [Small EV]							0.38	0.14–1.04	.059						
Skewness [Moderate] * Magnitude [Large EV]							1.05	0.41–2.71	.916						
Skewness [Strong] * Magnitude [Large EV]							0.93	0.36–2.41	.882						
Magnitude/Valence [–5]										2.31	0.49–11.01	.293	2.30	0.48–10.96	.296
Magnitude/Valence [–0.5]										5.10	0.98–26.52	.053	4.55	0.87–23.89	.073

Magnitude/Valence [+0.5]										3.09	0.61–15.59	.172	3.21	0.64–16.25	.158
Magnitude/Valence [+5]										4.16	0.84–20.67	.082	3.79	0.76–18.93	.104
Skewness [Moderate] * Magnitude/Valence [–5]										1.19	0.40–3.51	.751	1.19	0.40–3.50	.754
Skewness [Strong] * Magnitude/Valence [–5]										0.41	0.14–1.19	.099	0.41	0.14–1.18	.098
Skewness [Moderate] * Magnitude/Valence [–0.5]										0.47	0.14–1.58	.224	0.47	0.14–1.57	.221
Skewness [Strong] * Magnitude/Valence [–0.5]										0.19	0.05–0.63	**.007**	0.18	0.05–0.62	**.007**
Skewness [Moderate] * Magnitude/Valence [+0.5]										1.63	0.51–5.22	.409	1.63	0.51–5.21	.410
Skewness [Strong] * Magnitude/Valence [+0.5]										0.74	0.23–2.34	.606	0.74	0.23–2.33	.603
Skewness [Moderate] * Magnitude/Valence [+5]										0.91	0.30–2.77	.868	0.91	0.30–2.76	.866
Skewness [Strong] * Magnitude/Valence [+5]										3.32	0.99–11.13	.052	3.32	0.99–11.11	.052
Age													1.34	0.83–2.15	.227
Random Effects															
σ^2	3.29			3.29			3.29			3.29			3.29		
τ_{00}	8.15 $_{ID}$			8.12 $_{ID}$			8.06 $_{ID}$			8.33 $_{ID}$			8.34 $_{ID}$		
τ_{11}	0.03 $_{ID.Age}$														
ρ_{01}	1.00 $_{ID}$														
ICC				0.71			0.71			0.72			0.72		
N	210 $_{ID}$			210 $_{ID}$			210 $_{ID}$			210 $_{ID}$			210 $_{ID}$		
Observations	1890			1890			1890			1890			1890		
Marginal R^2 / Conditional R^2	0.015 / NA			0.037 / 0.722			0.023 / 0.717			0.050 / 0.731			0.056 / 0.733		