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Local Thinking and Skewness Preferences*

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Abstract

We show that continuous models of stimulus-driven attention can account for skewness-related puzzles in decision-making under risk. First, we delineate that these models provide a well-defined theory of choice under risk. We therefore prove that in continuous—in contrast to discrete—models of stimulus-driven attention each lottery has a unique certainty equivalent that is monotonic in probabilities (i.e., it monotonically increases if probability mass is shifted to more favorable outcomes). Second, we show that whether an agent seeks or avoids a specific risk depends on the skewness of the underlying probability distribution. Since unlikely, but outstanding payoffs attract attention, an agent exhibits a preference for right-skewed and an aversion toward left-skewed risks. While cumulative prospect theory can also account for such skewness preferences, it yields implausible predictions on their magnitude. We show that these extreme implications can be ruled out for continuous models of stimulus-driven attention.

JEL-Classification: D81.

Keywords: Stimulus-Driven Attention; Salience Theory; Focusing; Certainty Equivalent; Monotonicity; Skewness Preferences.

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1 Introduction

Few individuals are globally risk averse or risk seeking. Instead, many individuals buy insurance (i.e., behave risk averse) and gamble in casinos (i.e., behave risk seeking) at the same time. Whether an agent seeks or avoids a specific risk depends on the skewness of the underlying probability distribution. Typically, agents insure against large potential losses that rarely occur (e.g., Sydnor, 2010; Barseghyan *et al.*, 2013). For example, natural disasters belong to this group of left-skewed risks. At the same time, individuals seek right-skewed risks such as casino gambling according to which a large gain is realized with a very small probability (e.g., Golec and Tamarkin, 1998; Garrett and Sobel, 1999; Forrest *et al.*, 2002). The observation that agents tend to seek right-skewed and avoid left-skewed risks (e.g., Ebert and Wiesen, 2011; Ebert, 2015) is referred to as *skewness preferences*.

A compelling explanation for skewness preferences is still missing. As expected utility theory (EUT) implies a valuation for risky options that is linear in probabilities, it predicts either risk-averse *or* risk-seeking behavior. Thus, it cannot account for risk attitudes that depend on the skewness of a given probability distribution. In order to match experimental and empirical evidence, cumulative prospect theory (CPT; Tversky and Kahneman, 1992) has proposed a non-linear probability weighting. As a CPT agent overweights small probabilities by assumption, she exhibits a preference for right-skewed and an aversion toward left-skewed risks. This mechanism, however, does not offer any psychologically sound explanation for why skewness matters. In addition, cumulative prospect theory makes implausible predictions on the magnitude of skewness preferences (e.g., Rieger and Wang, 2006; Azevedo and Gottlieb, 2012; Ebert and Strack, 2015, 2016). Altogether, neither expected utility theory nor cumulative prospect theory convincingly address the role of skewness in choice under risk.

Models of stimulus-driven attention offer a more intuitive explanation for skewness preferences. According to these models, individuals are *local thinkers* whose attention is automatically directed toward certain outstanding choice features while less attention-grabbing aspects tend to be neglected.[1] Similar to cumulative prospect theory, these approaches incorporate probability weighting, but the distortion of a probability weight is endogenously determined by the relative size of the corresponding payoff. Probabilities of outstanding outcomes are inflated, while probabilities of less attention-grabbing outcomes are underweighted. In a typical lottery game, for instance, the large jackpot stands out relative to the rather low price of the lottery ticket, thereby attracting a great deal of attention. Overweighting the probability of winning the salient jackpot, a local thinker behaves risk seeking. In contrast, an agent typically demands insurance against unlikely, but potentially large losses. Compared to the rather small insurance premium the large loss stands out, its probability is inflated, and a local thinker behaves risk averse. Importantly, this line of argumentation holds for different models of stimulus-driven at-

[1] We have borrowed the notion of *local thinking* from a related model by Gennaioli and Shleifer (2010).

tention, that are, *salience theory of choice under risk* (Bordalo *et al.*, 2012, henceforth: BGS) and *a model of focusing* (Kőszegi and Szeidl, 2013, henceforth: KS). Accordingly, models of stimulus-driven attention can account for both a preference for right-skewed and an aversion toward left-skewed risks.

Our contributions in this paper are threefold. First, we show that continuous models of stimulus-driven attention satisfy basic axioms of choice under risk. In particular, for any lottery with finitely many outcomes, there exists a well-defined certainty equivalent that is monotonic in outcomes and probabilities. Kontek (2016) has shown that in discrete model variants (i) certainty equivalents may not exist and (ii) monotonicity in probabilities may be violated. These results hinge on the assumption that in the discrete salience model, for instance, the objective probability of the i^{th} most salient outcome is discounted via a factor δ^{i+1} for some salience-parameter $\delta < 1$. Then, for example, monotonicity in probabilities may be violated if the probability mass is shifted from a low, salient outcome to a larger but less salient outcome which is strongly discounted. BGS use the simplified, discrete version of their model for analytical ease which arguably, it is best thought of as an approximation to the more realistic, but also complex, continuous model. We show that all problems raised by Kontek are resolved in the continuous salience and focusing models.

Second, we show that models of stimulus-driven attention predict skewness preferences. For the discrete salience model, Bordalo *et al.* (2013a) have argued that salient thinkers like right-skewed and dislike left-skewed assets, but they have not precisely disentangled a salient thinker's preferences for risk and skewness. In contrast, we derive skewness preferences formally, that is, we show that a salient thinker is more likely to choose a binary risk if it is ceteris paribus (i.e., for a given expected value and variance) skewed further to the right. In addition, we single out the channel (*contrast effects*) through which the salience model predicts skewness preferences. The contrast effect means that, when comparing a risky and a safe option, a risky outcome receives the more attention the more it differs from the safe option's payoff. As the models of salience (BGS) and focusing (KS) share the assumption of contrast effects, both predict skewness preferences.

Third, we show that unrealistic predictions of cumulative prospect theory on the magnitude of skewness preferences (e.g., Rieger and Wang, 2006; Azevedo and Gottlieb, 2012; Ebert and Strack, 2015, 2016) can be resolved in the continuous salience and focusing models. For CPT agents, there always exists a sufficiently skewed, small binary risk with negative expected value that is attractive. As a consequence, a CPT agent either gambles until bankruptcy or, if she anticipates her behavior, never starts to gamble (Ebert and Strack, 2015, 2016). In addition, gambling at risk of an arbitrarily large expected loss may attract CPT agents (Rieger and Wang, 2006; Azevedo and Gottlieb, 2012). For appropriately chosen functional forms, models of stimulus-driven attention do not share these extreme predictions.

Beyond the examples given at the beginning of this paper, skewness preferences are also relevant in several other important economic—including many financial—decision situations. Barberis (2013), for instance, argues that skewness preferences can account for the puzzle that the average return of stocks conducting an initial public offering (IPO) is below that of comparable stocks that did not conduct an IPO. This could be explained by the fact that stocks that conduct an IPO are typically right-skewed and therefore overpriced (Boyer *et al.*, 2010; Bali *et al.*, 2011; Conrad *et al.*, 2013). In this line, Green and Hwang (2012) find that the more skewed the distribution of expected returns is, the lower the long-term average return of an IPO-stock is. Chen *et al.* (2001) even argue that managers strategically disclose information in order to create positive skewness in the distribution of stock returns. This also relates to the well-known growth puzzle (Fama and French, 1992) according to which value stocks, which are underpriced relative to financial indicators, yield higher average returns than (overpriced) growth stocks. Bordalo *et al.* (2013a) suggest that this discrepancy arises as value stocks are typically left-skewed while growth stocks are usually right-skewed. Relatedly, skewness preferences play an important role for portfolio selection (Chunhachinda *et al.*, 1997; Prakash *et al.*, 2003; Mitton and Vorkink, 2007). They further allow us to understand the prevalent use of technical analysis for asset trades, even though it is futile in light of the efficient market hypothesis (Ebert and Hilpert, 2016). Finally, a preference for skewness also matters in labor economics as Hartog and Vijverberg (2007) or Berkhout *et al.* (2010) argue that workers accept a lower expected wage if the distribution of wages in a cluster (i.e., education-occupation combination) is right-skewed. Altogether, skewness preferences help to understand various puzzles of economic decision-making.

We proceed as follows. Throughout the paper, we restrict our analysis to the model of salience (BGS) while we establish the analogous results for the focusing model (KS) in Appendix B. In Section 2, we present the continuous salience model. Subsequently, we prove that in this model a lottery has a well-defined certainty equivalent that satisfies monotonicity (Section 3). In Section 4, we show that the salience model predicts skewness preferences. In Section 5, we delineate that puzzles on the magnitude of skewness preferences emerging for CPT agents can be resolved in the salience model. Finally, Section 6 discusses our findings and concludes. All proofs are relegated to Appendix A.

2 Model

According to salience theory of choice under risk, a choice problem is defined by some choice set C, which contains a finite number of lotteries yielding risky monetary payoffs, and the corresponding space of states of the world S. Each state of the world corresponds to a payoff-combination of the available lotteries. Suppose an agent chooses a lottery from the set $C := \{L_x, L_y\}$ where $L_x := (x_1, p_1; \dots; x_n, p_n)$ and $L_y := (y_1, q_1; \dots; y_m, q_m)$ with $n, m \in \mathbb{N}$ and $\sum_{i=1}^{n} p_i = \sum_{i=1}^{m} q_i = 1$. Thereby the payoffs x_i denote pairwisely distinct monetary outcomes, which occur with strictly positive probabilities $p_i > 0$ for $1 \leq i \leq n$ (we impose analogous conventions for lottery L_y's outcomes). If a lottery is degenerate, we call it a *safe* option. The decision-maker evaluates monetary outcomes via a strictly increasing value function $u(\cdot)$ with $u(0) = 0$. Each state of the world $s_{ij} := (x_i, y_j)$ occurs with some objective probability π_{ij}. According to expected utility theory, lottery L_x's expected utility $U(\cdot)$ equals

$$U(L_x) = \sum_{s_{ij} \in S} \pi_{ij} u(x_i).$$

According to salience theory of choice under risk, a decision-maker evaluates a lottery by assigning a subjective probability to each state s_{ij} that depends on the state's objective probability π_{ij} and on its salience. In particular, the salience of state $s_{ij} \in S$ is determined by a symmetric, bounded, and continuously differentiable salience function $\sigma(\cdot, \cdot)$ that satisfies the following three properties:

1. *Ordering.* Let $\mu = \text{sgn}(u(x_i) - u(y_j))$. Then for any $\epsilon, \epsilon' \geq 0$ with $\epsilon + \epsilon' > 0$,

$$\sigma(u(x_i) + \mu\,\epsilon, u(y_j) - \mu\,\epsilon') > \sigma(u(x_i), u(y_j)).$$

2. *Diminishing sensitivity.* Let $u(x_i), u(y_j) \geq 0$. Then for any $\epsilon > 0$,

$$\sigma(u(x_i) + \epsilon, u(y_j) + \epsilon) < \sigma(u(x_i), u(y_j)).$$

3. *Reflection.* For any $u(x_i), u(y_j), u(x_k), u(y_l) \geq 0$, we have

$$\begin{aligned} & \sigma(u(x_i), u(y_j)) < \sigma(u(x_k), u(y_l)) \\ \text{if and only if} \qquad & \sigma(-u(x_i), -u(y_j)) < \sigma(-u(x_k), -u(y_l)). \end{aligned}$$

We say that a state s_{ij} is the more salient the larger its salience value $\sigma(u(x_i), u(y_j))$ is. Thus, the ordering property implies that a state is the more salient the more the lotteries' payoffs in this state differ. In this sense ordering captures the *contrast effect*, according to which a large difference in the values assigned to the outcomes in a given state attracts a salient thinker's attention.[2] Diminishing sensitivity reflects *Weber's law* of perception and implies that the salience of a state decreases if the outcomes' values uniformly increase in absolute terms. Hence diminishing sensitivity captures the *level effect* according to which a given contrast in the value of outcomes is more salient for lower outcome levels. As contrast and level effects are more intuitive and easier to understand than the properties of ordering and diminishing sensitivity, we refer to these notions whenever it is possible in the following analysis. Throughout the paper, we use $\sigma_{\beta,\theta}(x, y) := \frac{\beta(x-y)^2}{(|x|+|y|+\theta)^2}$ for some $\beta, \theta > 0$ as our leading example of a parametric salience function.

Following the smooth salience characterization proposed in Bordalo *et al.* (2012, page 1255), each state s_{ij} receives the salience weight $\Delta^{-\sigma(u(x_i), u(y_j))}$ for some salience function $\sigma(\cdot, \cdot)$ and some constant $\Delta \in (0, 1]$ that captures an agent's susceptibility to salience. A rational decision-maker is captured by $\Delta = 1$, while the smaller Δ is, the stronger the salience bias is. We call an agent with $\Delta < 1$ a *salient thinker*.

[2]If we fix one argument of the salience function then the ordering property is equivalent to the contrast effect, that is, the salience of a state increases if and only if the difference in values increases.

Definition 1. *A salient thinker's decision utility* $U^s(\cdot)$ *for* $L_x \in \{L_x, L_y\}$ *is given by*

$$U^s(L_x) = \sum_{s_{ij} \in S} \pi_{ij}\, u(x_i) \cdot \frac{\Delta^{-\sigma(u(x_i),u(y_j))}}{\sum_{s_{ij} \in S} \pi_{ij}\, \Delta^{-\sigma(u(x_i),u(y_j))}}.$$

This gives the decision utility according to the continuous model proposed by BGS, where the normalization factor in the denominator ensures that the distorted probabilities sum up to one. Note that for safe options $c \in \mathbb{R}$, we have $U^s(c) = U(c) = u(c)$. Hence, the normalization ensures that a salient thinker's valuation for a safe option c is undistorted, irrespective of the composition of the choice set.

Importantly, the results that we derive in this paper do not hinge on most assumptions specific to the above salience model, but hold for a broader class of models that exhibit contrast effects. We can relax, for instance, the assumption that agents evaluate lotteries based on the objective state space. Indeed, our results would be identical if the salient thinker considers a subset of the state space as long as each outcome of each option is included in (at least) one of this subset's states (see, for instance, the model variant proposed in Dertwinkel-Kalt and Köster, 2015). This is due to the fact that our analysis builds only on choices between a lottery and a safe option. In Appendix B, we further present the analogous results for the closely related focusing model (KS). According to focusing, an agent's attention directed to a given state is determined through a focusing function (i.e., the pendant to the salience function) that satisfies the contrast, but not the level effect.

3 Certainty equivalents and monotonicity

Models of choice under risk should allow certainty equivalents to be identified for all lotteries to ensure that a lottery's evaluation is well-defined. Certainty equivalents are typically required to satisfy the axiom of monotonicity according to which a lottery's certainty equivalent increases if either probability mass is shifted toward more favorable outcomes or if some outcomes increase. We precisely define these properties as follows.

Definition 2. *Let* $L := (x_1, p_1; \ldots; x_n, p_n)$ *denote some lottery with* $x_i \in \mathbb{R}$ *for all* $1 \leq i \leq n$. *Outcomes are ordered such that* $x_1 < \ldots < x_n$ *and probabilities* $p_1, \ldots, p_n$ *sum up to one.*

(a) *The* certainty equivalent *is defined as the minimum monetary sum c that makes a salient thinker indifferent between taking lottery L and getting c for sure. Formally, suppose an agent faces some choice set* $\{L, c\}$ *comprising a lottery L and a safe option c. Then c is the certainty equivalent to lottery L if and only if* $U^s(L) = U^s(c)$ *.*

(b) *Denote* $L' := (x_1, p_1'; \ldots; x_n, p_n')$ *where* $p_i' = p_i + \epsilon$ *and* $p_l' = p_l - \epsilon$ *for some* $i > l$ *and some* $\epsilon > 0$ *and* $p_k' = p_k$ *for all* $k \neq i, l$. *Suppose that c denotes the certainty equivalent to L and* c' *denotes the certainty equivalent to* L'. *The certainty equivalent is* monotonic in probabilities *if and only if* $c' > c$.

(c) *Denote* $L'' := (x''_1, p_1; \ldots; x''_n, p_n)$ *where* $x''_l > x_l$ *for some* $l \in \{1, \ldots, n\}$ *and* $x''_k = x_k$ *for all* $k \neq l$. *Suppose that* c *denotes the certainty equivalent to* L *and* c'' *denotes the certainty equivalent to* L''. *The certainty equivalent is* monotonic in outcomes *if and only if* $c'' > c$.

Kontek (2016) establishes that in the discrete salience model certainty equivalents do not satisfy monotonicity in probabilities and may not even exist. We will illustrate that these observations are artefacts of the simplified, discrete salience model that Kontek (2016) analyzes. Here, the objective probability of the i^{th} most salient outcome is discounted via a factor δ^{i+1} for some salience-parameter $\delta < 1$. Therefore, a change in the salience ranking of states induces a discontinuous jump in a salient thinker's valuation for a given lottery. As a consequence, for some lotteries a certainty equivalent may not exist.

For illustrative reasons, consider a binary lottery that pays \$1 with probability p and \$0 with probability $1-p$. If the lottery's upside of winning \$1 is unlikely (i.e., p is small), a certainty equivalent—being close to the downside of winning \$0—exists. Here, the lottery's upside is salient. If p increases gradually, the certainty equivalent increases likewise, which implies that the lottery's upside becomes less and its downside becomes more salient, which however does not alter the salience weights. Note that we can find some $\hat{p}$ for which a certainty equivalent exists and the lottery's up- and downside are equally salient. According to the discrete model, a salient thinker's valuation for the above lottery drops discontinuously at $p = \hat{p}$ because for larger p the downside becomes the most salient outcome. Hence, there exist some $\epsilon > 0$ such that for any $p \in [\hat{p} - \epsilon, \hat{p})$ no certainty equivalent exists (for a formal analysis, see Kontek, 2016). In addition, for lotteries with more than two outcomes, monotonicity in probabilities may be violated if probability mass is shifted from a low, salient outcome to a larger, but less salient outcome which is strongly discounted.

BGS apply the simplified, discrete version of their model for analytical ease when the continuous model would yield identical, but harder to derive, insights. In contrast, the above counterintuitive properties rely on the use of the discrete model. We resolve the issues of non-existing and non-monotonic certainty equivalents by investigating the more involved continuous salience model proposed in the previous section. First, we show that given continuous salience distortions each binary lottery has a well-defined certainty equivalent, which also satisfies monotonicity in probabilities and outcomes. Second, we generalize our findings toward lotteries with finitely many outcomes.

Binary lotteries. Suppose an agent faces a choice set $\{L, c\}$ where $L := (x_1, p; x_2, 1-p)$ is a binary lottery with $x_2 > x_1$ and c denotes the option that pays an amount of c with certainty. Then, lottery L is (weakly) preferred over the safe option c if and only if

$$U^s(c) \leq U^s(L) = \frac{u(x_1)\, p\, \Delta^{-\sigma(u(x_1),u(c))} + u(x_2)\, (1-p)\, \Delta^{-\sigma(u(x_2),u(c))}}{p\, \Delta^{-\sigma(u(x_1),u(c))} + (1-p)\, \Delta^{-\sigma(u(x_2),u(c))}} =: f(c),$$

while the safe option c is a salient thinker's certainty equivalent to lottery L if and only if

$$c = u^{-1}\left(f(c)\right).$$

For $p = 0$ the certainty equivalent is given by $c = u^{-1}(u(x_2)) = x_2$ while for $p = 1$ it is equal to $c = u^{-1}(u(x_1)) = x_1$. We conclude that the certainty equivalent—given it exists—lies between x_1 and x_2 for any $p \in (0,1)$ because $u^{-1}(\cdot)$ is strictly increasing and $U^s(L)$ is a convex combination of $u(x_1)$ and $u(x_2)$. Then,

$$u^{-1} \circ f : [x_1, x_2] \to [x_1, x_2], \quad c \mapsto u^{-1}(f(c))$$

is a well-defined continuous function on a closed, convex set which has—by Brouwer's fixed-point theorem—a fixed point. By the ordering property, $\sigma(u(x_1), u(c))$ strictly increases in c, while $\sigma(u(x_2), u(c))$ strictly decreases in c. It follows that $f(c)$ strictly decreases in c, so that the certainty equivalent is unique. Thus, for any $p \in [0,1]$ a well-defined certainty equivalent c exists.

In order to verify monotonicity in probabilities and outcomes, we define

$$h(x_1, x_2, p, c) := u^{-1}(f(c)) - c$$

where $c = c(x_1, x_2, p)$ denotes the unique certainty equivalent of lottery L. As ordering implies that $\sigma(u(x_1), u(c))$ strictly decreases in x_1 and $\sigma(u(x_2), u(c))$ strictly increases in x_2, we obtain that $f(c)$ strictly increases in x_k for $k \in \{1,2\}$. Remembering that $f(c)$ strictly decreases in c, we have

$$\frac{\partial h(x_1, x_2, p, c)}{\partial c} < 0 \quad \text{and} \quad \frac{\partial h(x_1, x_2, p, c)}{\partial x_k} > 0, \quad k \in \{1,2\}.$$

In addition, straightforward computations show that

$$\frac{\partial h(x_1, x_2, p, c)}{\partial p} = \underbrace{u'\left(f(c)\right)^{-1}}_{>0} \cdot \underbrace{\left(-\frac{\Delta_1 \Delta_2 (u(x_2) - u(x_1))}{(p\Delta_1 + (1-p)\Delta_2)^2}\right)}_{<0} < 0,$$

where $\Delta_k := \Delta^{-\sigma(u(x_k), u(c))}$ for $k \in \{1,2\}$. The implicit function theorem then yields

$$\frac{\partial c}{\partial p} = -\frac{\frac{\partial h(x_1,x_2,p,c)}{\partial p}}{\frac{\partial h(x_1,x_2,p,c)}{\partial c}} < 0 \quad \text{and} \quad \frac{\partial c}{\partial x_k} = -\frac{\frac{\partial h(x_1,x_2,p,c)}{\partial x_k}}{\frac{\partial h(x_1,x_2,p,c)}{\partial c}} > 0, \quad k \in \{1,2\}.$$

Hence a salient thinker's certainty equivalent to any binary lottery is well-defined and monotonic in probabilities and outcomes.

Lotteries with finitely many outcomes. We extend our preceding analysis and show that also for a more general, discrete lottery $L := (x_1, p_1; \ldots; x_n, p_n)$ with $n \geq 2$ pairwisely distinct outcomes, a certainty equivalent exists and is well-defined. Consider again some choice set $\{L, c\}$, where option c gives the monetary outcome c with certainty. A salient thinker (weakly) prefers lottery L to the safe option c if and only if

$$U^s(c) \leq U^s(L) = \frac{\sum_{i=1}^n p_i \, u(x_i) \Delta^{-\sigma(u(x_i),u(c))}}{\sum_{i=1}^n p_i \, \Delta^{-\sigma(u(x_i),u(c))}} =: f(c).$$

Furthermore, without loss of generality, we label outcomes such that $x_1 < \ldots < x_n$. Note that a salient thinker's certainty equivalent to L is implicitly given by $c = u^{-1}(f(c))$. Analogous to the case of a binary lottery, the continuous function $u^{-1} \circ f : [x_1, x_n] \to [x_1, x_n]$ has at least one fixed point due to Brouwer's fixed-point theorem and we obtain the following proposition.

Proposition 1 (Certainty equivalent to a discrete lottery)**.** *A salient thinker's certainty equivalent to a lottery with $n \geq 2$ outcomes is unique and monotonic in outcomes and probabilities.*

For a given lottery L, we can define a salient thinker's *risk premium* r as the difference in the lottery's expected value $\mathbb{E}[L]$ and its certainty equivalent c, that is $r := \mathbb{E}[L] - c$. Given Proposition 1, a salient thinker's risk premium for lottery L is well-defined. In the next section, we will investigate a salient thinker's risk preferences by determining the size and the sign of her risk premium.

4 Risk attitudes and skewness preferences

We investigate how salience shapes risk attitudes by analyzing under which conditions a salient thinker prefers a lottery over a safe option that pays the lottery's expected value. In Section 4.1, we show that salient thinkers are risk averse with respect to sufficiently left-skewed lotteries and risk seeking with respect to sufficiently right-skewed lotteries. This can explain the simultaneous demand for insurance and casino gambling. We thereby extend findings by BGS (see their Section IV) to the continuous salience model. In Section 4.2, we precisely show that salient thinkers exhibit a preference for skewness. While for general lotteries different notions of skewness exist, they coincide in the case of binary gambles. We therefore restrict attention to binary lotteries. These are uniquely characterized by their first three standardized central moments: expected value, variance, and skewness. Thus, we can precisely analyze a salient thinker's preferences over the skewness of lotteries. We relate our findings to the growing literature on skewness preferences.

4.1 Stylized facts on skewness preferences

Suppose a decision-maker decides whether to buy some binary lottery L at its fair price. Formally, the decision-maker faces the choice set $\{L, \mathbb{E}[L]\}$ where $L := (x_1, p; x_2, 1-p)$ is a binary lottery with outcomes $x_2 > x_1$ and the expected value $\mathbb{E}[L] := p \cdot x_1 + (1-p) \cdot x_2$. We refer to $\mathbb{E}[L]$ as the actuarially *fair price* of lottery L. In order to deal with indifference, we say that the decision-maker buys the lottery at its fair price if and only if she strictly prefers the risky option L over the safe option $\mathbb{E}[L]$.

In line with BGS, in this section we assume a linear value function $u(x) = x$.[3] Then, a salient thinker chooses the safe option over the risky lottery if and only if

$$p \cdot x_1 + (1-p) \cdot x_2 \geq \frac{p \cdot x_1 \cdot \Delta^{-\sigma(x_1,\mathbb{E}[L])} + (1-p) \cdot x_2 \cdot \Delta^{-\sigma(x_2,\mathbb{E}[L])}}{p \cdot \Delta^{-\sigma(x_1,\mathbb{E}[L])} + (1-p) \cdot \Delta^{-\sigma(x_2,\mathbb{E}[L])}}.$$

Rearranging this inequality gives $\Delta^{-\sigma(x_1,\mathbb{E}[L])} \geq \Delta^{-\sigma(x_2,\mathbb{E}[L])}$, or, equivalently,

$$\sigma(x_1, \mathbb{E}[L]) \geq \sigma(x_2, \mathbb{E}[L]).$$

Thus, whenever the lottery's downside x_1 is weakly more salient than its upside x_2, the agent behaves risk averse and prefers the safe option; otherwise, the agent chooses the risky lottery. This highlights a crucial difference in probability weighting under salience and cumulative prospect theory. While the CPT agent overweights small probabilities independent of the corresponding outcome's size, the salient thinker inflates decision weights on salient outcomes.

On the one hand, salience distortions can induce risk-averse behavior. For illustrative reasons, let $x_1 \geq 0$ and $p \leq 1/2$. This immediately implies $\mathbb{E}[L] - x_1 \geq x_2 - \mathbb{E}[L]$, that is, the contrast in the downside payoff and expected value exceeds the contrast in the upside payoff and expected value. Thus, we obtain

$$\begin{aligned} \sigma(x_1, \mathbb{E}[L]) &> \sigma(\mathbb{E}[L], \mathbb{E}[L] + \mathbb{E}[L] - x_1) \\ &\geq \sigma(\mathbb{E}[L], \mathbb{E}[L] + x_2 - \mathbb{E}[L]) \\ &= \sigma(x_2, \mathbb{E}[L]), \end{aligned}$$

where the first inequality follows from diminishing sensitivity, the second one from ordering, and the final equality from symmetry. We conclude that a salient thinker behaves risk averse if a non-negative downside payoff is (weakly) less likely than the upside payoff.

On the other hand, a salient thinker might be risk seeking. As before, suppose $x_1 \geq 0$. If the lottery's upside is unlikely but large compared to its expected value, the salient thinker might buy the lottery at its fair price. In fact, we can construct a binary lottery with a salient upside so that the salient thinker goes for the risky instead of the safe option. Note that ordering implies

$$\lim_{p \to 1} \sigma(x_2, \mathbb{E}[L]) = \sigma(x_2, x_1) > \sigma(x_1, x_1) = \lim_{p \to 1} \sigma(x_1, \mathbb{E}[L]).$$

Since the salience function is continuous, there exists some $\hat{p} = \hat{p}(x_1, x_2) \in (1/2, 1)$ such that for any $p > \hat{p}$ the lottery's upside is salient and the salient thinker chooses the risky option. Due to diminishing sensitivity, a salient thinker behaves risk seeking only if the lottery's upside x_2 occurs with a strictly lower probability than its non-negative downside

[3] In contrast to expected utility theory, salience theory does not have to assume a curved value function in order to generate risk-averse or risk-seeking behavior. As salience distortions suffice to generate different risk attitudes, the use of a linear value function is justified (Bordalo *et al.*, 2012).

x_1. More generally, we obtain the following proposition.[4]

Proposition 2 (Risk attitudes)**.** *Suppose a salient thinker chooses between the binary lottery* $L := (x_1, p; x_2, 1-p)$ *and the safe option that pays the lottery's expected value. Then, there exists some value* $\hat{p} = \hat{p}(x_1, x_2) \in (0, 1)$ *such that she prefers the safe option if and only if* $p \leq \hat{p}$.

Next, we relate a salient thinker's risk attitude to a lottery's skewness. Ebert (2015) defines the skewness of a binary lottery as its third, standardized central moment

$$S(L) := \mathbb{E}\left[\left(\frac{L - \mathbb{E}[L]}{\sqrt{Var(L)}}\right)^3\right] = \frac{2p-1}{\sqrt{p(1-p)}} \tag{1}$$

where $Var(L) := p(1-p)(x_2 - x_1)^2$ denotes the variance of lottery L. Other notions of skewness refer to "long and lean" tails of the risk's probability distribution. There exist several measures of skewness, which are, however, all equivalent for binary risks (Ebert, 2015, Proposition 2). Thus, the impact of skewness on risk attitudes can only be unambiguously assessed for binary lotteries. In the following, we adopt the short, intuitive notion of skewness which refers to the probability that the lottery's downside payoff is realized.

Definition 3 (Skewness of binary risks)**.** *Consider two binary lotteries* $L_x := (x_1, p; x_2, 1-p)$ *and* $L_y := (y_1, q; y_2, 1-q)$ *with* $x_2 > x_1$ *and* $y_2 > y_1$. *We say that* L_x *is more (less, equally) skewed than* L_y *if* $p > q$ $(p < q, p = q)$. *Lottery* L_x *is called right-skewed if* $p > \frac{1}{2}$, *left-skewed if* $p < \frac{1}{2}$ *and symmetric otherwise.*

From equation (1) it is straightforward to see that $S < 0$ for any left-skewed lottery, $S > 0$ for any right-skewed lottery and $S = 0$ for any symmetric lottery. Therefore, we also say that a left-skewed (right-skewed) lottery is *negatively* (*positively*) skewed and that a lottery is more skewed the larger S is.

The distribution of various downside risks such as car accidents or natural disasters is typically left-skewed: these events are rare, but if they happen they are severe. In this context, option $\mathbb{E}[L]$ may reflect a fair-priced insurance contract against the downside risk. The distribution of casino gambling, lottery games or specific investments, on the other hand, is typically right-skewed: gains are large, but occur rarely. Here, option $\mathbb{E}[L]$ can be interpreted as the fair price to bet on an upside risk.

The finding that agents seek right-skewed risks but tend to avoid left-skewed risks is established in the literature as skewness preferences. A tendency to choose right-skewed risks has been observed by Golec and Tamarkin (1998) with respect to horse-race betting, by Garrett and Sobel (1999) in the context of lottery games, and in several studies on investment behavior (Boyer *et al.*, 2010; Bali *et al.*, 2011; Green and Hwang, 2012; Conrad *et al.*, 2013). At the same time, consumers insure against left-skewed risks as demonstrated by Sydnor (2010) and Barseghyan *et al.* (2013) who analyze deductible choices in auto and

[4]BGS derive a similar result for the discrete salience model.

home insurance contracts. The following stylized examples illustrate that salience theory can account for this empirical evidence.[5]

Example 1 (Insurance). Suppose the agent has to decide whether to pay the fair insurance premium in order to avoid a binary risk L. In a typical insurance example, the risky option yields a large loss (i.e., $x_1 < 0$) with a small probability and zero payoff (i.e., $x_2 = 0$) otherwise. Then, according to Proposition 2, a salient thinker buys the insurance if the probability of the loss is sufficiently small.

Example 2 (Gambling). Suppose the agent decides whether to buy a lottery ticket at its fair price. When participating in the lottery, she could win either a large amount (i.e., $x_2 > 0$) or nothing (i.e., $x_1 = 0$). Due to diminishing sensitivity, the salient thinker might prefer the gamble only if the risk is right-skewed. According to Proposition 2, the salient thinker buys the lottery ticket if the probability of the gain is sufficiently small.

Example 3 (Investments). Suppose the agent decides whether to buy an asset—that either pays $x_1 < 0$ or $x_2 > 0$ in the future—at its fair price. If the probability of the gain is sufficiently high, the downside payoff x_1 stands out and the salient thinker does not invest in the asset. If the probability of the loss is high, the upside payoff x_2 is salient and the decision-maker buys the asset at its fair price. This implies a tendency to buy right-skewed assets, as Bordalo *et al.* (2013a) have already pointed out.[6]

4.2 Salience and skewness preferences

In line with the empirical evidence, salience theory suggests that the skewness of the risk's probability distribution affects risk attitudes. Most field studies, however, do not precisely test for the role of skewness in risk-taking as the variance and skewness of typical casino gambling or lottery games are not independent, but are highly correlated. Thus, risk and skewness preferences cannot be disentangled. Ebert (2015) argues, for instance, that inferring skewness preferences at the horse track from the study by Golec and Tamarkin (1998) might be misleading. In fact, increasing the skewness of a stylized horse race bet $L = (1/p, p; 0, 1 - p)$, while holding the expected value and the variance (i.e., the corresponding risk) constant, does not yield a new horse race bet, but a lottery with very different properties. Ebert (2015) concludes that "a choice between two horse-race bets is never a choice between different levels of skewness only."

[5]Notably, salience theory can also explain the demand for small scale insurance, e.g. insurance for consumption goods such as TVs or smartphones, where the potential loss is high relative to the insurance premium but not large overall. Cicchetti and Dubin (1994), for instance, report that many consumers pay a substantial premium in order to avoid the small risk (less than one percent) of having to pay $55 for repair in case their internal telephone wiring breaks down.

[6]While Bordalo *et al.* (2013a) state that salience predicts a "taste for skewness" in the context of asset choices, we will precisely disentangle a salient thinker's preferences for risk and skewness. Thereby, we are the first to formally derive a salient thinker's preference for skewness.

Hence, in order to disentangle a salient thinker's preference for skewness from her preference for risk, a lottery's skewness needs to be varied for a fixed expected value and variance. As for given outcomes x_1 and x_2 a change in the probability p also induces a change in the lottery's expected value $\mathbb{E}[L]$ and its variance $Var(L)$, we cannot infer from Proposition 2 whether it is the skewness of the risk that induces the aversion toward left-skewed and the preference for right-skewed lotteries.

Lemma 1 (Ebert (2015)'s moment characterization of binary risks)**.** *For constants $E \in \mathbb{R}$, $V \in \mathbb{R}_+$ and $S \in \mathbb{R}$, there exists exactly one binary lottery $L = (x_1, p; x_2, 1-p)$ with $x_2 > x_1$ such that $\mathbb{E}[L] = E$, $Var(L) = V$ and $S(L) = S$. Its parameters are given by*

$$x_1 = E - \sqrt{\frac{V(1-p)}{p}}, \; x_2 = E + \sqrt{\frac{Vp}{1-p}}, \; \text{and } p = \frac{1}{2} + \frac{S}{2\sqrt{4+S^2}}. \tag{2}$$

For a proof of Lemma 1 see Ebert (2015). In the following, we will refer to the unique binary lottery that has expected value E, variance V, and skewness S as $L(E, V, S)$. Using this moment characterization of binary risks, we can assess the impact of skewness on the salient thinker's risk attitude. As before, we assume $u(x) = x$ so that the salient thinker's risk premium for the binary lottery $L(E, V, S)$ equals

$$r(E, V, S) = \sqrt{Vp(1-p)} \cdot \left(\frac{\Delta^{-\sigma(x_1,E)} - \Delta^{-\sigma(x_2,E)}}{p\Delta^{-\sigma(x_1,E)} + (1-p)\Delta^{-\sigma(x_2,E)}} \right) \tag{3}$$

where outcomes $x_k = x_k(E, V, S)$, $k \in \{1, 2\}$, and probability $p = p(S)$ are defined in (2). A salient thinker strictly prefers the risky option $L(E, V, S)$ over the safe option E if and only if the lottery's risk premium is strictly negative, or, equivalently, its upside payoff is salient. We conclude:

Proposition 3 (Skewness preferences)**.** *For a given expected value E and variance V, there exists a unique skewness threshold value $\hat{S} = \hat{S}(E, V) < \infty$ such that $r(E, V, \hat{S}) = 0$. A salient thinker strictly prefers the binary lottery $L(E, V, S)$ over its expected value E if and only if $S > \hat{S}$.*

Suppose the lottery's expected value and variance are fixed. Then, by (2) increasing the lottery's skewness S increases the probability that its downside payoff is realized. If the lottery's downside payoff becomes more likely, the difference between its upside payoff and the expected value increases, thereby making the lottery's upside more salient. At the same time, the difference between the downside payoff and the expected value decreases so that the lottery's downside becomes less salient. Hence, a salient thinker is the more likely to take a binary risk the more skewed this risk is. By continuity of the salience function we obtain the following corollary.

Corollary 1. *For a given expected value E and variance V, there exists a sufficiently skewed binary lottery for which a salient thinker is willing to pay more than its fair price E.*

Comparative statics of the skewness threshold value. We briefly discuss how the threshold value $\hat{S}$ depends on the lottery's expected value E.

Lemma 2. *The threshold value $\hat{S}$ defined in Proposition 3 satisfies*

$$\frac{\partial}{\partial E}\hat{S}(E,V) < 0 \ \textit{ if and only if } \ \frac{\partial}{\partial E}\bigg(\sigma(x_2(E,V,S),E) - \sigma(x_1(E,V,S),E)\bigg)\bigg|_{S=\hat{S}} > 0.$$

We use the above Lemma to characterize the relationship between skewness preferences and expected payoffs using our leading example of a salience function, $\sigma_{\beta,\theta}$.

Corollary 2. *Consider the lottery $L(E,V,\hat{S})$ with outcomes $\hat{x}_k := x_k(E,V,\hat{S})$ for $k \in \{1,2\}$. For salience function $\sigma_{\beta,\theta}$ we obtain:*

$$\frac{\partial}{\partial E}\hat{S}(E,V) \begin{cases} > 0, & \textit{if } \hat{x}_1 < 0 < \hat{x}_2, \\ < 0, & \textit{otherwise.} \end{cases}$$

This implies that for any lottery with $\hat{x}_1 \geq 0$ or $\hat{x}_2 \leq 0$ skewness preferences become stronger if the lottery's expected value E increases in absolute terms. To see this, note that diminishing sensitivity implies $\hat{S} > 0$ if $\hat{x}_1 \geq 0$ while it yields $\hat{S} < 0$ if $\hat{x}_2 \leq 0$. Hence, for these lotteries, an absolute increase in the expected value E shifts the threshold value $\hat{S}$ closer to zero and thereby reinforces a salient thinker's preference for right-skewed and her aversion toward left-skewed risks. In contrast, for lotteries with $\hat{x}_1 < 0 < \hat{x}_2$ skewness preferences become stronger if the expected value decreases in absolute terms.

Skewness preferences and the contrast effect. Intuitively, in the salience model, skewness preferences are driven by the contrast effect. The stronger the contrast effect, the more pronounced is a large difference between a lottery's payoff and its expected value. For a positively skewed lottery, the upside payoff differs by more from the expected value than the downside payoff, while the opposite holds for a negatively skewed lottery. Therefore, if the contrast effect becomes stronger, a salient thinker's preference for positive skewness is enhanced. We formalize this idea as follows.

Definition 4. *We say that the contrast effect is stronger for salience function σ than for salience function $\hat{\sigma}$ if for any $y \in \mathbb{R}$ the difference $\sigma(x,y) - \hat{\sigma}(x,y)$ is increasing in $|x-y|$.*

The contrast between two values is typically measured by their difference. Thus, the preceding definition captures the intuitive notion that the contrast effect is stronger for one salience function than another if their difference (i.e., the difference in salience values) increases in the difference of their arguments.

Proposition 4 (Contrast and skewness preferences)**.** *Let the contrast effect be stronger for salience function σ than for salience function $\hat{\sigma}$. Then, a salient thinker's risk premium $r(E,V,S)$ is larger for σ than for $\hat{\sigma}$ if and only if $S < 0$, that is, the lottery is left-skewed.*

This implies that a stronger contrast effect enhances a salient thinker's aversion toward left-skewed risks and her preference for right-skewed risks. Since we derive the preference for skewness from lotteries with the same expected value, the salience function's second argument is held fixed so that the contrast effect is equivalent to the ordering property in this context. In other words, a salient thinker's preference for skewness is the stronger the more important ordering is relative to diminishing sensitivity. This is in line with the comparative statics results derived above. BGS have shown that, for any non-negative or non-positive arguments, the salience function $\sigma_{\beta,\theta}$ satisfies weaker diminishing sensitivity if its arguments uniformly increase in absolute terms.[7] According to Corollary 2, for any lottery with either non-negative or non-positive outcomes, skewness preferences are stronger if the lottery's expected value increases in absolute terms or, equivalently, ordering becomes more important relative to diminishing sensitivity.

Notably, as a model of focusing (KS) also builds on the contrast effect it shares all of our central results on skewness preferences (see Appendix B for a formal proof). In contrast, a model of relative thinking (Bushong *et al.*, 2016) that builds on the setup by KS, but assumes reverse contrast effects (i.e., attention assigned to a state decreases in the payoff range) cannot account for skewness preferences.

Experimental evidence on skewness preferences. Our preceding results are in line with experimental evidence on skewness preferences. In contrast to studies with field data, laboratory experiments allow us to precisely test for skewness preferences (i.e., the skewness of a lottery can be varied ceteris paribus). Ebert and Wiesen (2011) find that a majority of subjects chooses a right-skewed over a left-skewed binary lottery with the same expected value and variance.[8] They also show that prudence (i.e., $u'''(\cdot) < 0$) does not suffice to explain skewness preferences.[9] Ebert (2015) confirms this preference for right-skewed over left-skewed binary risks. In addition, he observes that a majority of subjects who have to choose between a symmetric and a right-skewed lottery, which has the same expected value and variance, opt for the more skewed alternative. If the choice is between a

[7]This follows from the fact that the salience function $\sigma_{\beta,\theta}$ is convex in the sense of BGS (see their Definition 3). Formally, a salience function is convex if and only if, for any $y, z \geq 0$ and $x, \epsilon > 0$, the difference $\sigma_{\beta,\theta}(y + x, z + x) - \sigma_{\beta,\theta}(y + x + \epsilon, z + x + \epsilon)$ is a decreasing function of x. From this definition it is straightforward to see that for any convex salience function diminishing sensitivity becomes weaker relative to ordering if x increases. Note that, for any $y, z \leq 0$ and $x, \epsilon < 0$, convexity of the salience function implies that the difference $\sigma_{\beta,\theta}(y + x, z + x) - \sigma_{\beta,\theta}(y + x + \epsilon, z + x + \epsilon)$ is an increasing function in x. Here, diminishing sensitivity is the weaker the smaller x is.

[8]More precisely, subjects have to choose between two binary lotteries that form a *Mao pair* (Mao, 1970). For any $p \in (0, 1/2)$, two perfectly correlated, binary lotteries $L_x := (x_1, p; x_2, 1-p)$ and $L_y := (y_1, 1-p; y_2, p)$ form a Mao pair if both have the same expected value and variance. Lotteries of a Mao pair differ only in their skewness (Ebert and Wiesen, 2011). Lottery L_x is left-skewed (i.e., its high payoff x_2 occurs with a high probability), while lottery L_y is right-skewed (i.e., its high payoff y_2 occurs with a small probability). In line with Definition 3, Ebert and Wiesen (2011) state that "an individual is said to be *skewness seeking* if, for any given Mao pair, she prefers L_y over L_x." In Appendix C we prove that, for any Mao pair, a salient thinker prefers L_y over L_x.

[9]Prudence can explain a preference for positive skewness given a fixed expected value and variance. While subjects making prudent choices also tend to choose right-skewed lotteries in the experiment by Ebert and Wiesen (2011), prudence is not sufficient to explain the number of skewness-seeking choices.

symmetric and a left-skewed lottery, subjects tend to avoid the left-skewed risk, thereby again choosing the more skewed lottery. Further studies using binary (e.g., Brünner *et al.*, 2011) or more complex lotteries (e.g., Grossman and Eckel, 2015) report similar results on skewness-seeking choices. In line with Proposition 3, Åstebro *et al.* (2015) observe that subjects tend to make riskier decisions if the choice set includes right-skewed lotteries. Altogether, a substantial body of research documents skewness preferences and related predictions under controlled conditions in the laboratory.

5 Puzzles on skewness preferences

In many respects, the predictions by salience theory of choice under risk coincide with the predictions by cumulative prospect theory (for a detailed discussion, see BGS). For instance, both theories predict that whether an agent buys insurance or prefers to gamble depends on the skewness of a risk. The skewness of a distribution may, however, induce implausible predictions for cumulative prospect theory, as shown by three articles. On the one hand, Ebert and Strack (2015) argue that for any value function (and any reference point), there exists a right-skewed and arbitrarily small binary risk with a negative expected value that is attractive to a CPT agent. This results in unrealistic predictions for dynamic investment or gambling decisions. On the other hand, Rieger and Wang (2006) as well as Azevedo and Gottlieb (2012) delineate that under "virtually all functional forms that have been proposed in the literature" (Azevedo and Gottlieb, 2012, page 1294) an CPT-agent's willingness to pay for a binary lottery with some fixed expected payoff is unbounded if the lottery's upside payoff becomes arbitrarily large. In the following, we will compare salience and cumulative prospect theory's predictions on skewness preferences in the small (Ebert and Strack, 2015) and in the large (Rieger and Wang, 2006; Azevedo and Gottlieb, 2012).

5.1 Skewness preferences in the small

Consider a dynamic setup where a decision-maker gambles according to the following strategy: she decides to start gambling, but will stop as soon as she has realized either a rather small loss x_1 or a large gain x_2. This stopping strategy with two absorbing endpoints can be represented as a binary lottery that gives a small loss with a large probability, and a large gain with a small probability. According to Corollary 1, a salient thinker is willing to pay more than the fair price to enter the corresponding gamble if this binary risk is sufficiently skewed. If the decision-maker is naïve and cannot commit to a long-run stopping strategy, but can revise her strategy after every single gain or loss, she never stops gambling as she can always construct a sufficiently skewed stopping strategy that attracts her. Independent of previous gains or losses, a salient thinker decides to gamble in every period anew and therefore continues until bankruptcy.

Likewise, CPT agents that cannot commit to a certain gambling strategy will gamble "until the bitter end" (Ebert and Strack, 2015). Ebert and Strack show that without commitment a naïve CPT agent that uses the preceding stopping strategy will never stop gambling irrespective of her value function's curvature.[10] In particular, Ebert and Strack (2015) verify that CPT agents reveal *skewness preferences in the small*: that is, sufficiently right-skewed binary lotteries with outcomes x_1 and x_2 that are sufficiently small in absolute terms are attractive even if these lotteries' expected values are negative. For these lotteries probability weighting may predominate loss aversion so that the CPT agent participates in an unfair gamble.

While even salient thinkers might gamble until the bitter end, the lotteries which are attractive to a salient thinker are fundamentally different. An attractive lottery's downside payoff should be close to the lottery's expected value, therefore being non-salient. At the same time, the upside payoff should be very large, thereby exceeding the expected value by much in order to stand out and attract the decision-maker's attention. Thus, it is not a preference for skewness in the small that induces a salient thinker to gamble until bankruptcy. It is a preference for lotteries with a large, outstanding upside payoff, which we regard as the more plausible driver of taking up unfair gambles. Forrest *et al.* (2002) precisely capture this intuition by stating that the purchase of a lottery ticket corresponds to "buying a dream." A decision-maker might dream of winning the large jackpot, which allows her to quit her tedious job or to buy an expensive car, thereby overweighting the probability that her dream will come true.

Cumulative prospect theory's prediction that an agent will, irrespective of her value function, play until bankruptcy has been regarded as implausible and therefore as a weakness of the model. We will show that the prediction does not necessarily hold for salient thinkers once the assumption of a linear value function has been dropped. Precisely, we investigate conditions under which Corollary 1 breaks down so that a salient thinker will not follow the above stopping strategy until her entire wealth is lost. In fact, if the value function is strictly concave, a salient thinker may or may not be inclined to gamble, depending on the interplay of her value function's and her salience function's curvature.[11]

Static salience predictions. Suppose a salient thinker faces some choice set $\{L, \mathbb{E}[L]\}$. For simplicity and in line with the gambling example, let $x_2 > x_1 \geq 0$. We drop our previous assumption of a linear value function and assume that the decision-maker's value from money is strictly increasing and strictly concave, that is, $u'(\cdot) > 0$ and $u''(\cdot) < 0$. As before, we normalize $u(0) = 0$. Then, a salient thinker strictly prefers the risky lottery L

[10] The naïve agent does not anticipate that she will not stick to her initial plan in the future. At every point in time, she constructs a new, attractive gambling strategy with negative expected value and continues gambling until she has lost her entire wealth. In contrast, a sophisticated agent who cannot commit to future behavior never starts to gamble (Ebert and Strack, 2016). The sophisticated agent is aware of her time-inconsistency and foresees that she will not stop gambling. Hence, she decides not to gamble in the first place.

[11] The fundamentals of the salience model, that is, the value function u, the salience function σ and the salience parameter Δ can be estimated simultaneously from real choice data as they are not perfectly collinear. Dertwinkel-Kalt *et al.* (2016a), for instance, conduct such an estimation for the closely related focusing model, simultaneously estimating the value and the focusing function.

over the safe option $\mathbb{E}[L]$ if and only if

$$\frac{u(x_2) - u(\mathbb{E}[L])}{u(\mathbb{E}[L]) - u(x_1)} \cdot \frac{1-p}{p} > \frac{\Delta_1}{\Delta_2},$$

where $\Delta_k := \Delta^{-\sigma(u(x_k), u(\mathbb{E}[L]))}$, $k \in \{1, 2\}$. For any given expected value $E = \mathbb{E}[L]$, substituting $p = (x_2 - E)/(x_2 - x_1)$ yields

$$\frac{\frac{u(x_2)-u(E)}{x_2-E}}{\frac{u(E)-u(x_1)}{E-x_1}} > \frac{\Delta_1}{\Delta_2}. \tag{C.1}$$

The left-hand side of this inequality constitutes the ratio of the secants' slopes through the points $(E, u(E))$ and $(x_k, u(x_k))$ for $k \in \{1, 2\}$, which is smaller than one for any strictly concave value function. The right-hand side of inequality (C.1) gives the ratio of the salience weights which is below one if and only if the lottery's upside is salient. Analogously to the previous section, we can conclude that the lottery's downside is salient whenever the lottery is left-skewed or symmetric.[12] While there exists a right-skewed lottery with a salient upside for any value function, it remains uncertain whether a salient thinker buys this lottery or not.

Intuitively, one would expect that condition (C.1) is less likely to hold if the value function's curvature increases as (context-independent) risk aversion becomes stronger. Compared to a linear value function, the contrast between the values assigned to the upside payoff and the expected value, respectively, is reduced. As the preference for skewness is driven by the contrast effect, salience distortions are weaker and are therefore less likely to induce risk-seeking behavior if the value function is concave. Indeed the left-hand side of (C.1) decreases in the value function's curvature. But the corresponding effect on the ratio of salience weights is ambiguous as it depends on how the relative importance of ordering and diminishing sensitivity changes with the level of values assigned to the outcomes. Therefore, it is impossible to make a general statement on how the value function's curvature affects a salient thinker's risk attitude (see Example 5 for an illustration).

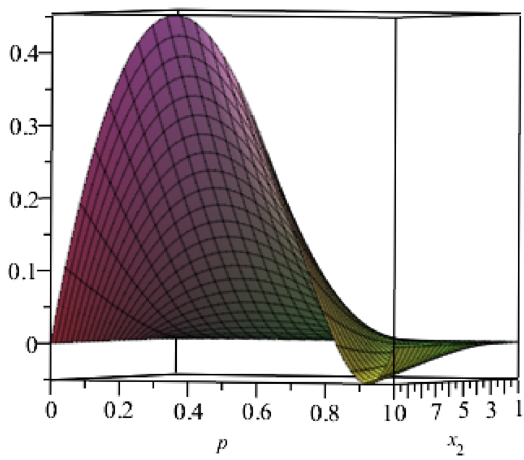
More can be said about the properties of the salience function that facilitate risk-seeking behavior. As established in Proposition 4, a salient thinker's preference for right-skewed risks is driven by the contrast effect. A salient thinker is especially prone to gambling if a large gain occurring with small probability stands in sharp contrast to the lottery's expected value, thereby grabbing much attention. Hence a salient thinker is the more risk seeking with respect to sufficiently right-skewed lotteries the stronger the contrast effect is relative to the level effect. In order to verify this intuition for a concave value function, we compare salience functions that differ in the strength of the contrast effect.

[12] Note that $u(E) - u(x_1) \geq u(x_2) - u(E)$ for any $p \leq 1/2$ due to strict concavity of the value function. Then, diminishing sensitivity implies that the lottery's downside is weakly more salient than its upside since $u(x_2) > u(x_1) \geq 0$ holds by assumption.

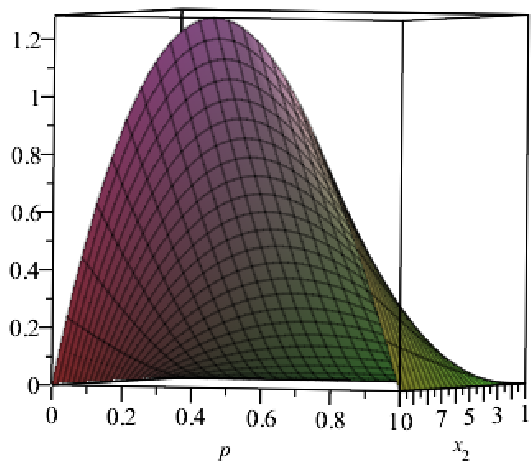
Proposition 5. *Let the contrast effect be stronger for salience function σ than for salience function $\hat{\sigma}$. If lottery L satisfies (C.1) for salience function $\hat{\sigma}$, it also satisfies (C.1) for salience function σ.*

If the value function is very concave and the salience function exhibits a weak contrast effect, there exists no lottery that the agent prefers to its expected value (i.e., condition (C.1) is never satisfied). We show this with the use of two examples for which we assume power utility $u(x) = x^\alpha$ with $\alpha \in (0, 1)$ and our standard salience function $\sigma_{\beta,\theta}(x, y)$ with $\beta, \theta > 0$. Let $\theta = 0.1$ and $\Delta = 0.7$.

Example 5 (Value function). For a linear value function, the left-hand side of (C.1) equals one and the salient thinker chooses a lottery if its upside is salient. This lottery exists by Proposition 3. Then, due to continuity, condition (C.1) also holds for a mildly concave value function $u(x) = x^\alpha$ with α being close to one. Let $\beta = 1$ so that the salience function is $\sigma_{\beta,\theta}(x, y) = \frac{(x-y)^2}{(|x|+|y|+0.1)^2}$. If the value function's curvature increases, that is, the parameter α decreases, we observe that inequality (C.1) is less likely to hold. More specifically, numerical computations show that there exists some threshold value $\hat{\alpha} \in (0, 1)$ such that for any $\alpha \in (0, \hat{\alpha})$ no unfair, attractive gamble exists. For $\alpha = 0.95$ and $\alpha = 0.5$, Figure 1 illustrates the risk premium r as a function of probability p and upside payoff x_2 for a given downside payoff $x_1 = 1$.



Risk premium for $\alpha = 0.95$.



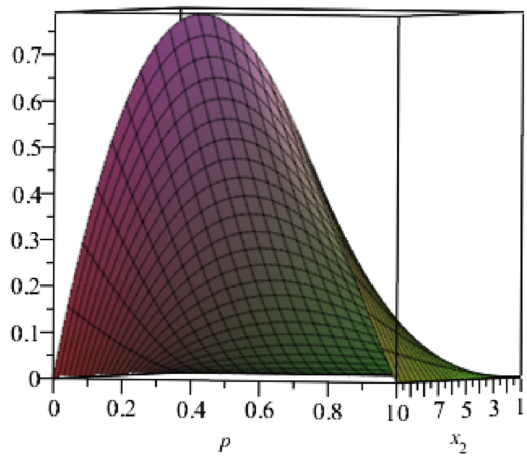
Risk premium for $\alpha = 0.5$.

Figure 1: *The above graphs show the risk premium as a function of the upside payoff x_2 and the probability p that the downside payoff x_1 is realized. For $\alpha = 0.95$, the risk premium becomes negative for highly right-skewed lotteries (i.e., a large probability p on the downside payoff x_1) with a large upside payoff x_2. For $\alpha = 0.5$, the risk premium is non-negative for any feasible lottery.*

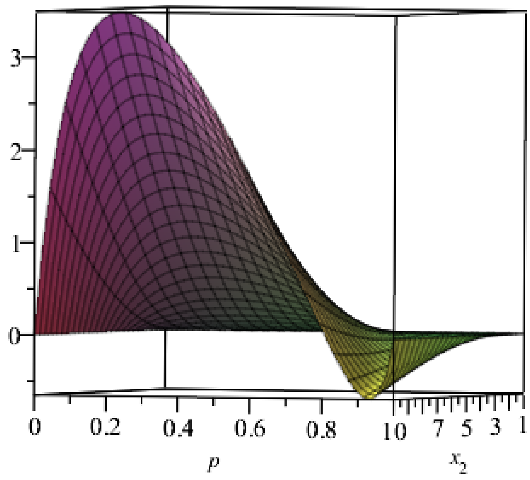
Example 6 (Salience function). Fix $\alpha = 3/4$ so that the value function is $u(x) = x^{3/4}$. We observe that inequality (C.1) is more likely to hold for at least some binary lottery L if parameter β increases.[13] In fact, numerical computations show that there exists some

[13] The larger β is the stronger is the contrast effect for salience function $\sigma_{\beta,\theta}$. This, however, holds only using the following notion of a stronger contrast effect which is weaker than that stated in Definition 4: for

$\hat{\beta} > 1$ such that for any $\beta > \hat{\beta}$ at least one unfair, attractive gamble exists. For $\beta = 1$ and $\beta = 10$, Figure 2 illustrates the risk premium r as a function of probability p and upside payoff x_2 for a given downside payoff $x_1 = 1$.



Risk premium for $\beta = 1$.



Risk premium for $\beta = 10$.

Figure 2: *The above graphs show the risk premium as a function of the upside payoff x_2 and the probability p that the downside payoff x_1 is realized. For $\beta = 10$, the risk premium becomes negative for highly right-skewed lotteries (i.e., a large probability p on the downside payoff x_1) with a large upside payoff x_2. For $\beta = 1$, the risk premium is non-negative for any feasible lottery.*

Comparison to the discrete salience model. Note that for the discrete salience model there always exists an unfair, binary lottery with a salient upside that is attractive to a salient thinker. This result is driven by the fact that for a lottery with a salient upside the right-hand side of inequality (C.1) simplifies to the salience-parameter $\delta < 1$ (as introduced in the discussion of the discrete salience model after Definition 2). Therefore, the right-hand side of inequality (C.1) is bounded away from one, while its left-hand side approaches one if the variance of lottery L goes to zero. Thus, the resolution of Ebert and Strack (2015)'s skewness puzzle relies on the use of the continuous salience model.

Dynamic salience predictions under asset integration. Suppose the decision-maker asset integrates—that is, she evaluates a lottery's outcomes not separately, but based on the wealth levels the lottery potentially induces. Again we consider a naïve agent who does not anticipate that she will not stick to her initial plan in the future. If a naïve salient thinker asset integrates, she may follow the delineated stopping strategy only until a certain wealth level has been reached. We briefly discuss for which wealth levels an unfair, but attractive binary lottery might exist. Whether such a lottery exists for a particular wealth level depends on how the value function's and the salience function's curvature change in wealth. First, suppose the value function satisfies decreasing absolute risk aver-

any $\beta > \tilde{\beta}$ and $x, y, z \in \mathbb{R}$, we have $\sigma_{\beta,\theta}(x, z) - \sigma_{\tilde{\beta},\theta}(x, z) > \sigma_{\beta,\theta}(y, z) - \sigma_{\tilde{\beta},\theta}(y, z)$ if $x > y \geq z$ or $x < y \leq z$.

sion. For a suitable salience function, it may be the case that a salient thinker gambles only at high wealth levels, but stops after her wealth has sufficiently decreased. Second, if the value function satisfies increasing absolute risk aversion the opposite may arise: if the agent's wealth increases, her value function's relative curvature increases as well and it becomes more likely that no binary lottery satisfies inequality (C.1). The salient thinker then stops gambling if her wealth is sufficiently large. In contrast, for low wealth levels the curvature of the agent's value function is weak such that inequality (C.1) is more likely to hold for at least some lottery. This observation relates to the *disposition effect* (Shefrin and Statman, 1985; Odean, 1998) according to which private investors are more inclined to sell assets that have increased in value than assets which have decreased in value. Thus, salience theory might account for the disposition effect under certain circumstances.

5.2 Skewness preferences in the large

Rieger and Wang (2006) and Azevedo and Gottlieb (2012) have shown that cumulative prospect theory also yields implausible predictions for right-skewed lotteries with large absolute payoffs. Denote $\mathcal{L}(E)$ as the set of all binary lotteries with some expected value $E \in \mathbb{R}$. Azevedo and Gottlieb (2012) argue that the expected gain that can be earned by selling a lottery $L \in \mathcal{L}(E)$ to a CPT agent may be unbounded. This prediction arises from the fact that probability weighting might induce an unbounded valuation of a lottery with finite expected value (Rieger and Wang, 2006). If small probabilities are overweighted, increasing the upside payoff and reducing the corresponding probability can make a lottery more attractive. This allows a firm to realize arbitrarily large gains if it offers a binary lottery with an arbitrarily large upside payoff (*skewness preferences in the large*).

We show that this puzzle can be resolved for salient thinkers as long as we consider only lotteries with a bounded expected value. Restricting our analysis to lotteries with a bounded expected value makes sense for the following two reasons: first, Rieger and Wang (2006) argue that it is practically not feasible for a firm to offer a lottery with a very large expected value. Second, a consumer with a constrained budget is not able to pay a very large price to participate in a lottery.

As before, suppose the decision-maker has a (weakly) concave value function and faces some choice set $\{L, z\}$ where z denotes the price of lottery L. The agent buys the lottery as long as it is strictly preferred over the monetary sum z. Since the salience function is bounded, there exists some threshold value $\bar{\Delta} < \infty$ such that $\Delta^{-\sigma(x,y)} < \bar{\Delta}$ for any $(x, y) \in \mathbb{R}^2$. The following proposition states that for any expected value E, the price a salient thinker is willing to pay for lottery $L \in \mathcal{L}(E)$ is bounded.

Proposition 6. *Let $\mathcal{L}(E)$ denote the set of binary lotteries L with finite expected value $E \in \mathbb{R}$. A salient thinker's valuation for some $L \in \mathcal{L}(E)$ is bounded by a function which is affine in E.*

Suppose a firm offers a binary lottery $L \in \mathcal{L}(E)$ at some price z. Optimally, it will set a price equal to the lottery's certainty equivalent, which is well-defined according to Proposition 1. Therefore, the firm will, for a given E, choose to sell that lottery $L \in \mathcal{L}(E)$

that has the largest certainty equivalent. According to Proposition 6, this is bounded such that the gain a firm can earn from selling a lottery with a fixed expected value cannot become arbitrarily large.[14]

6 Discussion and Conclusion

We have identified the *contrast effect* as a plausible driver of skewness preferences. According to the contrast effect, when comparing a risky and a safe option, a risky outcome receives the more attention the more it differs from the safe option's payoff. Thereby, the contrast effect induces a focus on the large but unlikely upside gain in the case of right-skewed risks, and a focus on the large potential loss in the case of left-skewed risks. As a consequence, salience theory and related approaches to local thinking that incorporate contrast effects, such as a model of focusing, predict a preference for positive skewness. In contrast, *a model of relative thinking* (Bushong *et al.*, 2016) that assumes reverse contrast effects (i.e., the weight assigned to a risky outcome decreases in its contrast to the safe option's payoff) cannot account for skewness preferences.

Models of local thinking offer an explanation for skewness preferences that fundamentally differs from approaches previously proposed in the literature. According to cumulative prospect theory, for instance, an agent exhibits a preference for skewness because she overweights small probabilities *per se*. In contrast, local thinkers overweight a small probability *only if the corresponding payoff stands out*. This mechanism of probability weighting is not only psychologically sound, but also allows for more realistic predictions. If the agent's value function becomes more concave, large payoffs are less attractive and less attention-grabbing so that also the corresponding probabilities are less distorted. Thereby, local thinking in combination with a concave value function rules out cumulative prospect theory's implausible predictions on the magnitude of skewness preferences (Rieger and Wang, 2006; Azevedo and Gottlieb, 2012; Ebert and Strack, 2015, 2016). Dynamically, a naïve CPT agent will never stop gambling until bankruptcy and will buy, but never exercise American options on assets (Ebert and Strack, 2015). Conversely, if the CPT agent is aware of her time-inconsistent behavior, she will not even acquire an option or start to gamble (Ebert and Strack, 2016). These predictions stand in stark contrast to robust empirical findings such as the disposition effect that states that options are exercised, assets are sold and gambles are quit if gains can be realized. As we have delineated, our explanation for skewness preferences does not necessarily go along with such drastic predictions. Concludingly, models of local thinking offer a more compelling explanation for skewness preferences than cumulative prospect theory.

Our approach has also advantages over other behavioral explanations for skewness preferences such as the model on optimal expectations proposed by Brunnermeier and Parker (2005). Here, an agent receives utility not only from her actions, but also from her

[14] Note, however, that the profit that can be earned from selling a lottery $L \in \bigcup_{E\in\mathbb{R}} \mathcal{L}(E)$ is unbounded.

beliefs over favorable future outcomes. Therefore, an agent inflates the "perceived likelihood" of upside events in order to enhance the pleasure from expecting these events. As a consequence, the demand for right-skewed lotteries is excessive. This model, however, yields weaker predictions on skewness preferences than our approach (see Proposition 2 in Brunnermeier and Parker, 2005). First, Brunnermeier and Parker explain an affection toward sufficiently right-skewed risks, but they do not obtain precise predictions on the demand for less skewed or left-skewed assets. Second, the puzzle investigated by Ebert and Strack (2015) cannot be resolved in their framework as long as the value function is unbounded. Finally, utility from pleasant expectations can be obtained only *before* an event is realized. Thus, it is plausible that optimal expectations matter only when there is some considerable amount of time between an investment decision and the event realization. Models of local thinking instead can explain skewness preferences irrespective of whether the realization of outcomes is delayed or not.

Besides skewness preferences, local thinking can account for a wide range of decision anomalies. In particular the salience model explains biases such as the Allais paradox (Bordalo *et al.*, 2012), decoy effects (Bordalo *et al.*, 2013b) and the newsvendor problem (Dertwinkel-Kalt and Köster, 2016) in one coherent framework, thereby challenging cumulative prospect theory as the major behavioral model of individual decision-making. Its assumptions have been supported both by empirical (Hastings and Shapiro, 2013) and experimental (Dertwinkel-Kalt *et al.*, 2016b) work. Consequently, models that build on the assumption of stimulus-driven attention are promising candidates for improving our predictions on when agents seek and when they shy away from risk.

Appendix A: Proofs

Proof of Proposition 1. Consider some discrete lottery $L := (x_1, p_1; \ldots; x_n, p_n)$ with $n \geq 2$. Denote $\Delta_i := \Delta^{-\sigma(u(x_i),u(c))}$ and $\sigma^i := \sigma(u(x_i), u(c))$ as well as $\sigma_x^i := \frac{\partial \sigma^i}{\partial u(x_i)}$ and $\sigma_y^i := \frac{\partial \sigma^i}{\partial u(c)}$.

First we verify that the certainty equivalent is unique. For that, it is sufficient to show

$$\frac{\partial U^s(L)}{\partial u(c)} = -\ln(\Delta) \left(\frac{\left(\sum_{k=1}^n p_k\, u(x_k)\Delta_k \sigma_y^k\right)\left(\sum_{k=1}^n p_k\, \Delta_k\right) - \left(\sum_{k=1}^n p_k \Delta_k \sigma_y^k\right)\left(\sum_{k=1}^n p_k\, u(x_k)\Delta_k\right)}{\left(\sum_{k=1}^n p_k\, \Delta_k\right)^2} \right) < 0.$$

Now it is straightforward to see that $\frac{\partial U^s(L)}{\partial u(c)} < 0$ holds if and only if

$$\underbrace{\frac{\sum_{k=1}^n p_k\, u(x_k)\Delta_k}{\sum_{k=1}^n p_k\, \Delta_k}}_{=u(c)} \left(\sum_{k=1}^n p_k \Delta_k \sigma_y^k \right) > \sum_{k=1}^n p_k\, u(x_k)\Delta_k \sigma_y^k.$$

Denote $\underline{X} := \{k \in \{1, \ldots, n\} | u(x_k) \leq u(c)\}$ and $\overline{X} := \{k \in \{1, \ldots, n\} | u(x_k) > u(c)\}$. Then, we can rewrite the above inequality as

$$\sum_{k \in \underline{X}} p_k\, \Delta_k \underbrace{\sigma_y^k}_{\geq 0} \underbrace{(u(c) - u(x_k))}_{\geq 0} + \sum_{k \in \overline{X}} p_k\, \Delta_k \underbrace{\sigma_y^k}_{<0} \underbrace{(u(c) - u(x_k))}_{<0} > 0.$$

Hence, $\frac{\partial U^s(L)}{\partial u(c)} < 0$ always holds and the certainty equivalent is unique.

Second, we verify that the certainty equivalent is monotonic in outcomes. Denote

$$H(\mathbf{x}, \mathbf{p}, c) := u^{-1} \left(\frac{\sum_{i=1}^n p_i\, u(x_i)\Delta^{-\sigma(u(x_i),u(c))}}{\sum_{i=1}^n p_i\, \Delta^{-\sigma(u(x_i),u(c))}} \right) - c,$$

where $\mathbf{x} := (x_1, \ldots, x_n)$, $\mathbf{p} := (p_1, \ldots, p_n)$. Then, we observe that

$$\frac{\partial}{\partial c} H(\mathbf{x}, \mathbf{p}, c) = \underbrace{(u^{-1})'\,(U^s(L))}_{>0} \underbrace{u'(c)}_{>0} \underbrace{\frac{\partial U^s(L)}{\partial u(c)}}_{<0} - 1 < 0 \tag{C.2}$$

and

$$\frac{\partial}{\partial x_k} H(\mathbf{x}, \mathbf{p}, c) = \underbrace{(u^{-1})'\,(U^s(L))}_{>0} \underbrace{u'(x_k)}_{>0} \frac{\partial U^s(L)}{\partial u(x_k)}$$

where

$$\frac{\partial U^s(L)}{\partial u(x_k)} = \frac{[p_k\Delta_k - p_k\Delta_k \ln(\Delta)\sigma_x^k u(x_k)]\left(\sum_{i=1}^n p_i\, \Delta_i\right) - [p_k\Delta_k(-\ln(\Delta))\sigma_x^k]\left(\sum_{i=1}^n p_i\, u(x_i)\Delta_i\right)}{\left(\sum_{i=1}^n p_i\, \Delta_i\right)^2}.$$

Thus, we have $\frac{\partial U^s(L)}{\partial u(x_k)} > 0$ if and only if

$$p_k\Delta_k \left[1 - \ln(\Delta)\sigma_x^k u(x_k) \right] > p_k\Delta_k(-\ln(\Delta))\sigma_x^k \underbrace{\left(\frac{\sum_{i=1}^n p_i\, u(x_i)\Delta_i}{\sum_{i=1}^n p_i\, \Delta_i} \right)}_{=u(c)}$$

or, equivalently,

$$1 + \underbrace{\ln(\Delta)}_{<0} \; \underbrace{\sigma_x^k \big(u(c) - u(x_k)\big)}_{\leq 0} > 0.$$

This inequality is always fulfilled as $\sigma_x^k \geq 0$ holds if and only if $u(c) \leq u(x_k)$. Hence, we have $\partial H(\mathbf{x}, \mathbf{p}, c)/\partial x_k > 0$ and the implicit function theorem yields monotonicity in outcomes, that is,

$$\frac{\partial c}{\partial x_k} = -\frac{\frac{\partial H(\mathbf{x},\mathbf{p},c)}{\partial x_k}}{\frac{\partial H(\mathbf{x},\mathbf{p},c)}{\partial c}} > 0.$$

Third, we assess whether the certainty equivalent is also monotonic in probabilities. Suppose that probability mass is c.p. shifted from outcome x_l to outcome x_i for some $i, l \in \{1, \ldots, n\}$, $i \neq l$. By definition, a salient thinker's certainty equivalent is monotonic in probabilities if and only if

$$\frac{\partial c}{\partial p_i} > 0 \Leftrightarrow x_i > x_l.$$

Denote $p_l = 1 - \sum_{j \neq l} p_j$ so that an increase in p_i induces a corresponding decrease in p_l. The implicit function theorem yields

$$\frac{\partial c}{\partial p_i} = -\frac{\frac{\partial H(\mathbf{x},\mathbf{p},c)}{\partial p_i}}{\frac{\partial H(\mathbf{x},\mathbf{p},c)}{\partial c}}.$$

Using ineq. (C.2) the certainty equivalent is monotonic in probabilities if and only if

$$\frac{\partial H(\mathbf{x}, \mathbf{p}, c)}{\partial p_i} > 0 \Leftrightarrow x_i > x_l.$$

Suppose $x_i > x_l$. Then we observe that

$$\frac{\partial H(\mathbf{x}, \mathbf{p}, c)}{\partial p_i} = \underbrace{(u^{-1})'\,(U^s(L))}_{>0} \left(\frac{[u(x_i)\ \Delta_i - u(x_l)\ \Delta_l] \sum_{k=1}^n (p_k\ \Delta_k) - [\Delta_i - \Delta_l] \sum_{k=1}^n (p_k\ u(x_k)\Delta_k)}{\left(\sum_{k=1}^n p_k\ \Delta_k\right)^2} \right) > 0,$$

which holds if and only if

$$\big(u(x_i) - u(c)\big)\Delta_i > \big(u(x_l) - u(c)\big)\Delta_l. \tag{C.3}$$

We distinguish the following three cases:

(1) $x_i > x_l > c$: In this case $u(x_i) - u(c) > u(x_l) - u(c) > 0$ and $\Delta_i > \Delta_l$ due to ordering. Thus, (C.3) is satisfied.

(2) $x_i > c > x_l$: The left-hand side of (C.3) is positive, while its right-hand side is negative, so that inequality (C.3) holds.

(3) $c > x_i > x_l$: Here, $0 > u(x_i) - u(c) > u(x_l) - u(c)$ and $\Delta_i < \Delta_l$ due to ordering which gives $(u(x_i) - u(c))\Delta_i > (u(x_i) - u(c))\Delta_l > (u(x_l) - u(c))\Delta_l$.

The case $x_i < x_l$ is analogous. Altogether, we conclude

$$\frac{\partial H(\mathbf{x}, \mathbf{p}, c)}{\partial p_i} > 0 \quad \text{if and only if} \quad x_i > x_l.$$

This completes the proof. □

Proof of Proposition 2. Let $L := (x_1, p; x_2, 1-p)$ with $x_2 > x_1$. Ordering implies

$$\lim_{p \to 0} \sigma(x_1, \mathbb{E}[L]) = \sigma(x_1, x_2) > \sigma(x_2, x_2) = \lim_{p \to 0} \sigma(x_2, \mathbb{E}[L]).$$

Since the salience function is continuous, there exists some $\hat{p} = \hat{p}(x_1, x_2) \in (0, 1)$ such that the lottery's downside is weakly more salient than its upside for any $p \leq \hat{p}$. Then, the statement immediately follows from the fact that—due to ordering—the salience of the lottery's downside payoff x_1 monotonically decreases in the probability p, while the salience of its upside payoff monotonically increases in p. □

Proof of Proposition 3. Consider a binary lottery L with expected value E and variance V. For a given skewness S, its parameters x_1, x_2 and p are uniquely defined as delineated in Lemma 1. Now suppose the lottery's skewness increases. Then, we observe that the lottery's downside payoff becomes more likely. Formally, we have

$$\frac{\partial p}{\partial S} = 2 \cdot (S^2 + 4)^{-3/2} > 0.$$

Using (2), this implies that both the downside payoff x_1 and the upside payoff x_2 increase in the skewness S. Therefore, the difference between the downside (upside) payoff and the expected value decreases (increases) in the lottery's skewness S. Formally, we have

$$\frac{\partial (E - x_1)}{\partial S} < 0 \quad \text{and} \quad \frac{\partial (x_2 - E)}{\partial S} > 0.$$

Since the expected value E is fixed, an increase in contrast is equivalent to an increase in salience due to ordering. Hence, the downside payoff's salience decreases in S, while the upside payoff's salience increases in S.

Since $\lim_{S \to \infty} x_2 = \infty > E$, we obtain

$$\lim_{S \to \infty} \sigma(x_2, E) > \sigma(E, E) = \lim_{S \to \infty} \sigma(x_1, E)$$

by the ordering property. Now by continuity of the salience function we can conclude that there exists some $\hat{S} < \infty$ such that for any $S > \hat{S}$ the lottery's upside is salient. As we have seen that the salience of both outcomes is monotonic in the lottery's skewness S, we conclude that the salient thinker chooses the risky option if and only if $S > \hat{S}$. Finally, $\lim_{S \to -\infty} \sigma(x_1, E) > \sigma(E, E) = \lim_{S \to -\infty} \sigma(x_2, E)$ and monotonicity ensure that there exists a unique skewness value $\hat{S} \in \mathbb{R}$ such that $r(E, V, \hat{S}) = 0$. □

Proof of Lemma 2. Consider the lottery $L(E,V,S)$, which has outcomes $x_k = x_k(E,V,S)$, $k \in \{1,2\}$, and a downside probability $p = p(S)$ as defined in (2). We divide the proof into two parts. First, we investigate how the salient thinker's risk premium $r(E,V,S)$ depends on the lottery's expected value E. Second, we use this result to prove our lemma.

PART (1). We need to determine the sign of

$$\frac{\partial}{\partial E} r(E,V,S) = \sqrt{Vp(1-p)} \cdot \frac{\partial}{\partial E}\left(\frac{\Delta^{-\sigma(x_1,E)} - \Delta^{-\sigma(x_2,E)}}{p\Delta^{-\sigma(x_1,E)} + (1-p)\Delta^{-\sigma(x_2,E)}}\right), \tag{4}$$

which equals the sign of

$$\frac{\partial}{\partial E}\left(\frac{\Delta_1 - \Delta_2}{p\Delta_1 + (1-p)\Delta_2}\right) = \frac{\left(\frac{\partial \Delta_1}{\partial E} - \frac{\partial \Delta_2}{\partial E}\right)(p\Delta_1 + (1-p)\Delta_2) - (\Delta_1 - \Delta_2)\left(p\frac{\partial \Delta_1}{\partial E} + (1-p)\frac{\partial \Delta_2}{\partial E}\right)}{(p\Delta_1 + (1-p)\Delta_2)^2} \tag{5}$$

with $\Delta_k := \Delta^{-\sigma(x_k,E)}$ for $k \in \{1,2\}$. Plugging

$$\frac{\partial \Delta_k}{\partial E} = -\ln(\Delta)\Delta_k \frac{\partial}{\partial E}\sigma(x_k,E)$$

into (5) yields

$$\frac{\partial}{\partial E}\left(\frac{\Delta_1 - \Delta_2}{p\Delta_1 + (1-p)\Delta_2}\right) = \underbrace{\frac{-\ln(\Delta)\Delta_1\Delta_2}{(p\Delta_1 + (1-p)\Delta_2)^2}}_{>0} \cdot \left(\frac{\partial}{\partial E}\sigma(x_1,E) - \frac{\partial}{\partial E}\sigma(x_2,E)\right).$$

Hence, we conclude

$$\frac{\partial}{\partial E} r(E,V,S) < 0 \quad \text{if and only if} \quad \frac{\partial}{\partial E}\left(\sigma(x_2,E) - \sigma(x_1,E)\right) > 0.$$

PART (2). By definition, the threshold value $\hat{S} = \hat{S}(E,V)$ solves $r = r(E,V,S) = 0$. Applying the implicit function theorem yields

$$\frac{\partial \hat{S}}{\partial E} = -\left.\frac{\frac{\partial}{\partial E} r(E,V,S)}{\frac{\partial}{\partial S} r(E,V,S)}\right|_{S=\hat{S}}.$$

Thus, we have to determine the sign of

$$\left.\frac{\partial r}{\partial S}\right|_{S=\hat{S}} = \sqrt{V}\underbrace{\left(\frac{\hat{\Delta}_1 - \hat{\Delta}_2}{p\hat{\Delta}_1 + (1-p)\hat{\Delta}_2}\right)}_{=0 \text{ by definition of } \hat{S}} \cdot \frac{\partial}{\partial S}\left(\sqrt{p(1-p)}\right)\Big|_{S=\hat{S}} + \sqrt{Vp(1-p)} \cdot \underbrace{\frac{\partial}{\partial S}\left(\frac{\Delta_1 - \Delta_2}{p\Delta_1 + (1-p)\Delta_2}\right)\Big|_{S=\hat{S}}}_{=:\Psi(E,V,\hat{S})}$$

where $\hat{\Delta}_k := \Delta^{-\sigma(x_k(E,V,\hat{S}),E)}$ for $k \in \{1,2\}$. Hence, we only need to derive the sign of

$$\Psi(E,V,\hat{S}) = \frac{\left(p\hat{\Delta}_1 + (1-p)\hat{\Delta}_2\right)\left(\frac{\partial \Delta_1}{\partial S} - \frac{\partial \Delta_1}{\partial S}\right)\Big|_{S=\hat{S}} + \overbrace{\left(\hat{\Delta}_1 - \hat{\Delta}_2\right)}^{=0 \text{ by def. of } \hat{S}}\left(p\frac{\partial \Delta_1}{\partial S} + (1-p)\frac{\partial \Delta_2}{\partial S} + \frac{\partial p}{\partial S}(\Delta_1 - \Delta_2)\right)\Big|_{S=\hat{S}}}{\left(p\hat{\Delta}_1 + (1-p)\hat{\Delta}_2\right)^2}$$

which is equivalent to the sign of

$$\left(\frac{\partial \Delta_1}{\partial S} - \frac{\partial \Delta_2}{\partial S}\right)\bigg|_{S=\hat{S}} = -\ln(\Delta)\hat{\Delta}_1\left(\frac{\partial}{\partial S}\sigma(x_1,E) - \frac{\partial}{\partial S}\sigma(x_2,E)\right)\bigg|_{S=\hat{S}}.$$

We conclude

$$\frac{\partial}{\partial S}\sigma(x_1,E)\bigg|_{S=\hat{S}} = -\frac{\sqrt{V}}{2\sqrt{\left(\frac{1-p}{p}\right)}}\frac{\partial\left(\frac{1-p}{p}\right)}{\partial S}\frac{\partial}{\partial x_1}\sigma(x_1,E)\bigg|_{S=\hat{S}}$$

and

$$\frac{\partial}{\partial S}\sigma(x_2,E)\bigg|_{S=\hat{S}} = \frac{\sqrt{V}}{2\sqrt{\left(\frac{p}{1-p}\right)}}\frac{\partial\left(\frac{p}{1-p}\right)}{\partial S}\frac{\partial}{\partial x_2}\sigma(x_2,E)\bigg|_{S=\hat{S}}.$$

Altogether, we have

$$\left(\frac{\partial \Delta_1}{\partial S} - \frac{\partial \Delta_2}{\partial S}\right)\bigg|_{S=\hat{S}} = -\ln(\Delta)\hat{\Delta}_1\sqrt{V}\frac{\partial\left(\frac{p}{1-p}\right)}{\partial S}\left(\sqrt{\frac{p}{1-p}}\overbrace{\frac{\partial}{\partial x_1}\sigma(x_1,E)}^{<0 \text{ due to ordering}} - \sqrt{\frac{1-p}{p}}\overbrace{\frac{\partial}{\partial x_2}\sigma(x_2,E)}^{>0 \text{ due to ordering}}\right)\bigg|_{S=\hat{S}} < 0$$

since $\frac{\partial\left(\frac{p}{1-p}\right)}{\partial S} = -\frac{\partial\left(\frac{1-p}{p}\right)}{\partial S} > 0$. This implies $\frac{\partial r}{\partial S}\big|_{S=\hat{S}} < 0$. Using PART (1), we obtain

$$\frac{\partial \hat{S}}{\partial E} < 0 \text{ if and only if } \frac{\partial}{\partial E}\Big(\sigma(x_2(E,V,S),E) - \sigma(x_1(E,V,S),E)\Big)\bigg|_{S=\hat{S}} > 0.$$

□

Proof of Corollary 2. Suppose salience function $\sigma_{\beta,\theta}(x,y) = \frac{\beta(x-y)^2}{(|x|+|y|+\theta)^2}$ for some $\beta,\theta > 0$. Consider the lottery $L(E,V,S)$ and denote $\hat{x}_k := x_k(E,V,\hat{S})$, $k \in \{1,2\}$, where $\hat{S}$ is defined in Proposition 3. We distinguish the following three cases.

CASE (1). Suppose $x_2 > x_1 \geq 0$. Then, using (2), we obtain

$$\sigma_{\beta,\theta}(x_2,E) - \sigma_{\beta,\theta}(x_1,E) = \frac{\beta V p}{(1-p)\left(E + \sqrt{\frac{Vp}{1-p}} + E + \theta\right)^2} - \frac{\beta V(1-p)}{p\left(E - \sqrt{\frac{V(1-p)}{p}} + E + \theta\right)^2}.$$

Now taking the partial derivative with respect to E yields

$$\begin{aligned}\frac{\partial}{\partial E}\Big(\sigma_{\beta,\theta}(x_2,E) - \sigma_{\beta,\theta}(x_1,E)\Big) &= \frac{-4\beta V p}{(1-p)\left(E+\sqrt{\frac{Vp}{1-p}}+E+\theta\right)^3} + \frac{4\beta V(1-p)}{p\left(E-\sqrt{\frac{V(1-p)}{p}}+E+\theta\right)^3} \\ &= \frac{4\sigma_{\beta,\theta}(x_1,E)}{E-\sqrt{\frac{V(1-p)}{p}}+E+\theta} - \frac{4\sigma_{\beta,\theta}(x_2,E)}{E+\sqrt{\frac{Vp}{1-p}}+E+\theta}.\end{aligned}$$

By definition of $\hat{S}$, we have $\sigma_{\beta,\theta}(\hat{x}_1,E) = \sigma_{\beta,\theta}(\hat{x}_2,E)$. Thus, it follows

$$\frac{\partial}{\partial E}\Big(\sigma_{\beta,\theta}(x_2,E) - \sigma_{\beta,\theta}(x_1,E)\Big)\bigg|_{S=\hat{S}} = \sigma_{\beta,\theta}(\hat{x}_1,E)\left(\frac{4}{E - \sqrt{\frac{V(1-p)}{p}} + E + \theta} - \frac{4}{E + \sqrt{\frac{Vp}{1-p}} + E + \theta}\right) > 0.$$

By Lemma 2, we conclude $\frac{\partial \hat{S}}{\partial E} < 0$.

CASE (2). Let $x_2 > 0 > x_1$. First, consider the subcase with $E > 0$. Then, we have

$$\begin{aligned} \sigma_{\beta,\theta}(x_2, E) - \sigma_{\beta,\theta}(x_1, E) &= \frac{\beta V p}{(1-p)\left(E+\sqrt{\frac{Vp}{1-p}}+E+\theta\right)^2} - \frac{\beta V(1-p)}{p\left(-\left(E-\sqrt{\frac{V(1-p)}{p}}\right)+E+\theta\right)^2} \\ &= \frac{\beta V p}{(1-p)\left(E+\sqrt{\frac{Vp}{1-p}}+E+\theta\right)^2} - \frac{\beta V(1-p)}{p\left(\sqrt{\frac{V(1-p)}{p}}+\theta\right)^2}. \end{aligned}$$

according to (2). Thus, we obtain

$$\frac{\partial}{\partial E}\left(\sigma_{\beta,\theta}(x_2, E) - \sigma_{\beta,\theta}(x_1, E)\right) = \frac{-4\beta V p}{(1-p)\left(E+\sqrt{\frac{Vp}{1-p}}+E+\theta\right)^3} < 0$$

for any $x_2 > 0 > x_1$ and $\frac{\partial \hat{S}}{\partial E} > 0$ follows from the proof of Lemma 2.

Second, consider the subcase with $E < 0$. Then, using equation (2), we obtain

$$\begin{aligned} \sigma_{\beta,\theta}(x_2, E) - \sigma_{\beta,\theta}(x_1, E) &= \frac{\beta V p}{(1-p)\left(E+\sqrt{\frac{Vp}{1-p}}+-E+\theta\right)^2} - \frac{\beta V(1-p)}{p\left(-\left(E-\sqrt{\frac{V(1-p)}{p}}\right)+-E+\theta\right)^2} \\ &= \frac{\beta V p}{(1-p)\left(\sqrt{\frac{Vp}{1-p}}+\theta\right)^2} - \frac{\beta V(1-p)}{p\left(-E+\sqrt{\frac{V(1-p)}{p}}-E+\theta\right)^2}. \end{aligned}$$

Thus, we have

$$\frac{\partial}{\partial E}\left(\sigma_{\beta,\theta}(x_2, E) - \sigma_{\beta,\theta}(x_1, E)\right) = -\frac{4\beta V(1-p)}{p\left(-E+\sqrt{\frac{V(1-p)}{p}}-E+\theta\right)^3} < 0$$

for any $x_2 > 0 > x_1$ and again $\frac{\partial \hat{S}}{\partial E} > 0$ follows from the proof of Lemma 2.

CASE (3). Suppose $x_1 < x_2 \leq 0$. Then, using equation (2), we obtain

$$\sigma_{\beta,\theta}(x_2, E) - \sigma_{\beta,\theta}(x_1, E) = \frac{\beta V p}{(1-p)\left(-\left(E+\sqrt{\frac{Vp}{1-p}}\right)-E+\theta\right)^2} - \frac{\beta V(1-p)}{p\left(-\left(E-\sqrt{\frac{V(1-p)}{p}}\right)-E+\theta\right)^2}.$$

Analogously to CASE (1), we have

$$\frac{\partial}{\partial E}\left(\sigma_{\beta,\theta}(x_2, E) - \sigma_{\beta,\theta}(x_1, E)\right) = \frac{4\sigma_{\beta,\theta}(x_2, E)}{-E-\sqrt{\frac{Vp}{1-p}}-E+\theta} - \frac{4\sigma_{\beta,\theta}(x_1, E)}{-E+\sqrt{\frac{V(1-p)}{p}}-E+\theta}.$$

By definition of $\hat{S}$, it holds that $\sigma_{\beta,\theta}(\hat{x}_1, E) = \sigma_{\beta,\theta}(\hat{x}_2, E)$. Thus, it follows

$$\frac{\partial}{\partial E}\left(\sigma_{\beta,\theta}(x_2, E) - \sigma_{\beta,\theta}(x_1, E)\right)\Big|_{S=\hat{S}} = \sigma_{\beta,\theta}(\hat{x}_1, E)\left(\frac{4}{-E-\sqrt{\frac{Vp}{1-p}}-E+\theta} - \frac{4}{-E+\sqrt{\frac{V(1-p)}{p}}-E+\theta}\right) > 0.$$

By Lemma 2, we conclude $\frac{\partial \hat{S}}{\partial E} < 0$. □

Proof of Proposition 4. Consider two salience functions σ and $\hat{\sigma}$. Suppose that the contrast effect is stronger for salience function σ than for salience function $\hat{\sigma}$. For the binary lottery L with expected value E, variance V, and skewness S, denote $r(E, V, S)$ the risk premium if the salience of outcomes is assessed via σ and $\hat{r}(E, V, S)$ the risk premium if the salience of outcomes is assessed via $\hat{\sigma}$. Then, it holds $r(E, V, S) > \hat{r}(E, V, S)$ if and only if

$$\frac{\sqrt{Vp(1-p)}(\Delta_1 - \Delta_2)}{p\Delta_1 + (1-p)\Delta_2} > \frac{\sqrt{Vp(1-p)}(\hat{\Delta}_1 - \hat{\Delta}_2)}{p\hat{\Delta}_1 + (1-p)\hat{\Delta}_2} \tag{C.4}$$

where $\Delta_k := \Delta^{-\sigma(x_k,E)}$ and $\hat{\Delta}_k := \Delta^{-\hat{\sigma}(x_k,E)}$ for $k \in \{1, 2\}$. Rewriting (C.4) gives

$$\frac{\Delta_1/\Delta_2 - 1}{p\Delta_1/\Delta_2 + (1-p)} > \frac{\hat{\Delta}_1/\hat{\Delta}_2 - 1}{p\hat{\Delta}_1/\hat{\Delta}_2 + (1-p)}$$

or, equivalently,

$$\frac{\Delta_1}{\Delta_2} > \frac{\hat{\Delta}_2}{\hat{\Delta}_2}.$$

Then, applying the definition of salience weights yields

$$\Delta^{-\sigma(x_1,E)+\sigma(x_2,E)} > \Delta^{-\hat{\sigma}(x_1,E)+\hat{\sigma}(x_2,E)},$$

which holds if and only if

$$\sigma(x_2, E) - \sigma(x_1, E) < \hat{\sigma}(x_2, E) - \hat{\sigma}(x_1, E).$$

Rearranging this inequality gives

$$\sigma(x_2, E) - \hat{\sigma}(x_2, E) < \sigma(x_1, E) - \hat{\sigma}(x_1, E).$$

This holds if and only if

$$\sqrt{\frac{Vp}{1-p}} = x_2 - E < E - x_1 = \sqrt{\frac{V(1-p)}{p}} \tag{C.5}$$

since the contrast effect is stronger for σ than for $\hat{\sigma}$. Finally, we conclude that (C.5) holds if and only if $p < 1/2$ or, equivalently, $S < 0$. By Definition 3, this is the case if and only if the lottery $L(E, V, S)$ is left-skewed. □

Proof of Proposition 5. For $x_2 > x_1 \geq 0$, let lottery $L := (x_1, p; x_2, 1-p)$ satisfy condition (C.1) given salience function $\hat{\sigma}$. Then, it is immediate that the upside of lottery L is salient under salience function $\hat{\sigma}$. As a consequence, it has to hold that

$$u(x_2) - u(\mathbb{E}[L]) > u(\mathbb{E}[L]) - u(x_1). \tag{C.6}$$

To see this, assume the opposite. Then, since $u(x_2) > u(x_1) \geq 0$, we have

$$\begin{aligned}\hat{\sigma}(u(x_1), u(\mathbb{E}[L])) &> \hat{\sigma}(u(\mathbb{E}[L]), u(\mathbb{E}[L]) + u(\mathbb{E}[L]) - u(x_1)) \\ &\geq \hat{\sigma}(u(\mathbb{E}[L]), u(\mathbb{E}[L]) + u(x_2) - u(\mathbb{E}[L])) \\ &= \hat{\sigma}(u(x_2), u(\mathbb{E}[L])),\end{aligned}$$

where the first inequality follows from diminishing sensitivity, the second one from ordering, and the final equality from symmetry. This yields a contradiction to the fact that the upside of lottery L is salient.

From condition (C.6), we conclude

$$\sigma(u(x_2), u(\mathbb{E}[L])) - \hat{\sigma}(u(x_2), u(\mathbb{E}[L])) > \sigma(u(x_1), u(\mathbb{E}[L])) - \hat{\sigma}(u(x_1), u(\mathbb{E}[L]))$$

by Definition 4 as the contrast effect is stronger for salience function σ than for salience function $\hat{\sigma}$. Rearranging the above inequality yields

$$\sigma(u(x_2), u(\mathbb{E}[L])) - \sigma(u(x_1), u(\mathbb{E}[L])) > \hat{\sigma}(u(x_2), u(\mathbb{E}[L])) - \hat{\sigma}(u(x_1), u(\mathbb{E}[L])).$$

As $\Delta < 1$ and $\hat{\sigma}(u(x_2), u(\mathbb{E}[L])) > \hat{\sigma}(u(x_1), u(\mathbb{E}[L]))$ we conclude

$$\Delta^{\sigma(u(x_2), u(\mathbb{E}[L])) - \sigma(u(x_1), u(\mathbb{E}[L]))} < \Delta^{\hat{\sigma}(u(x_2), u(\mathbb{E}[L])) - \hat{\sigma}(u(x_1), u(\mathbb{E}[L]))}.$$

Thus, if lottery L satisfies condition (C.1) for salience function $\hat{\sigma}$, then lottery L also satisfies condition (C.1) for salience function σ. This completes the proof. □

Proof of Proposition 6. For a given expected value $E \in \mathbb{R}$, consider a lottery $L \in \mathcal{L}(E)$ which is sold at some price $z \in \mathbb{R}$. Hence the choice set comprises $\{L, z\}$. As u is concave there exist some $a, b \geq 0$ such that $u(x) \leq ax + b$. Denote $\Delta_k := \Delta^{-\sigma(u(x_k), u(z))}$ for $k \in \{1, 2\}$. Using $p = (x_2 - E)/(x_2 - x_1)$ we get

$$\begin{aligned}U^s(L) =& \frac{\Delta_1(x_2 - E)u(x_1) + \Delta_2(E - x_1)u(x_2)}{\Delta_1(x_2 - E) + \Delta_2(E - x_1)} \\ \leq& \frac{\Delta_1(x_2 - E)(ax_1 + b) + \Delta_2(E - x_1)(ax_2 + b)}{\Delta_1(x_2 - E) + \Delta_2(E - x_1)} \\ =& b + a \cdot \frac{\Delta_1(x_2 - E)x_1 + \Delta_2(E - x_1)x_2}{\Delta_1(x_2 - E) + \Delta_2(E - x_1)} \\ \leq& b + a\bar{\Delta} \cdot \frac{(x_2 - E)x_1 + (E - x_1)x_2}{x_2 - x_1} \\ =& b + a\bar{\Delta}E.\end{aligned}$$

Here, the first inequality follows from the concavity of the value function, while the second inequality follows from using the upper bound of $\bar{\Delta}$ for the salience weights in the numerator and the lower bound of 1 for the salience weights in the denominator. □

Appendix B: Skewness preferences according to a model of focusing (Kőszegi and Szeidl, 2013)

In this section, we verify that our explanation for skewness preferences does not hinge on the specific assumptions of salience theory of choice under risk, but also holds under a related approach to stimulus driven attention—*a model of focusing* (Kőszegi and Szeidl, 2013). As Kőszegi and Szeidl analyze deterministic choice problems only, we extend their model toward risky choices along the lines of salience theory, that is, the agent evaluates an option according to the underlying state space. As discussed in Section 2, this assumption can be relaxed for both the salience and the focusing model.

Model. Suppose some choice set $C := \{L_x, L_y\}$ where $L_x := (x_1, p_1; \ldots, x_n; p_n)$ and $L_y := (y_1, q_1; \ldots; y_m, q_m)$ are discrete lotteries with $n, m \in \mathbb{N}$ and $\sum_{i=1}^{n} p_i = \sum_{i=1}^{m} q_i = 1$. We impose the same conventions for the lotteries' outcomes as in the main text (i.e., the lotteries' ouctomes are pairwisely distinct and occur with strictly positive probability). The state space S comprises all feasible payoff-combinations of the available lotteries. Thereby, each state of the world $s_{ij} := (x_i, y_j)$ occurs with some objective probability π_{ij}. Again we assume that the decision-maker evaluates monetary outcomes via a strictly increasing value function $u(\cdot)$ with $u(0) = 0$.

According to the focusing model, a decision-maker assigns a weight to each state s_{ij} that depends on the state's objective probability π_{ij} and on the absolute difference in the values of the feasible outcomes in this state, denoted as $d_{ij} := |u(x_i) - u(y_j)|$. The larger the range of values assigned to the outcomes in a state is, the higher the agent's focus on this particular state. Formally, the agent's focus on state $s_{ij} \in S$ is given by $g(d_{ij})$ where the focusing function $g : \mathbb{R}_+ \to \mathbb{R}_+$ is bounded and strictly increasing.[15]

For reasons of comparability, we adopt the smooth salience characterization introduced in Section 2 for the focusing model. That is, each state s_{ij} receives focus weight $\Delta^{-g(d_{ij})}$ for some focusing function $g(\cdot)$ and some constant $\Delta \in (0, 1]$ that captures the agent's susceptibility to focusing. We call an agent with $\Delta < 1$ a *focused thinker*.

Definition 5. *A focused thinker's decision utility $U^f(\cdot)$ for $L_x \in \{L_x, L_y\}$ is given by*

$$U^f(L_x) = \sum_{s_{ij} \in S} \pi_{ij} u(x_i) \cdot \frac{\Delta^{-g(d_{ij})}}{\sum_{s_{ij} \in S} \pi_{ij} \Delta^{-g(d_{ij})}}.$$

The normalization factor in the denominator ensures that the distorted probabilities sum up to one and that the valuation for a safe option $c \in \mathbb{R}$ is undistorted; that is, irrespective of the composition of the choice set we have $U^f(c) = U(c) = u(c)$.

[15] Relatedly, Bushong *et al.* (2016) propose *a model of relative thinking* that differs from the preceding focusing model only in the assumption on the slope of g: while we have $g'(d_{ij}) > 0$ for the focusing model, we have $g'(d_{ij}) < 0$ for the model of relative thinking. In words, a relative thinker's probability weight on state s_{ij} decreases in the corresponding absolute difference in values d_{ij}.

Certainty equivalents and monotonicity. Suppose the agent faces some choice set $\{L, c\}$ where $L := (x_1, p_1; \ldots; x_n, p_n)$ is a lottery with $n \geq 2$ pairwisely distinct ouctomes and c denotes the option that pays an amount of $c \in \mathbb{R}$ with certainty. A focused thinker (weakly) prefers the lottery L over the safe option c if and only if

$$U^f(c) \leq U^f(L) = \frac{\sum_{i=1}^{n} p_i u(x_i) \Delta^{-g(|u(x_i)-u(c)|)}}{\sum_{i=1}^{n} p_i \Delta^{-g(|u(x_i)-u(c)|)}} =: F(c).$$

Without loss of generality we assume $x_1 < \ldots < x_n$. Then a focused thinker's certainty equivalent is implicitly given by $c = u^{-1}(F(c))$. As for the salience model, we conclude that $u^{-1} \circ F : [x_1, x_n] \to [x_1, x_n]$ has at least one fixed point due to Brouwer's fixed-point theorem and we obtain the following proposition.

Proposition 7 (Certainty equivalent to a discrete lottery)**.** *A focused thinker's certainty equivalent to a lottery with $n \geq 2$ outcomes is unique and monotonic in outcomes and probabilities.*

Proof. Note that for any salience function $\sigma(\cdot, \cdot)$ and any focusing function $g(\cdot)$ we have

$$sgn\left(\frac{\partial \sigma(u(x_i), u(c))}{\partial u(x_i)}\right) = sgn\left(\frac{\partial g(|u(x_i) - u(c)|)}{\partial u(x_i)}\right) \quad \text{and} \quad sgn\left(\frac{\partial \sigma(u(x_i), u(c))}{\partial u(c)}\right) = sgn\left(\frac{\partial g(|u(x_i) - u(c)|)}{\partial u(c)}\right).$$

Then, the statement simply follows from replacing the salience function in the proof of Proposition 1 by a focusing function. □

Skewness preferences under a linear value function. To investigate a focused thinker's attitude toward skewness, suppose some choice set $\{L, \mathbb{E}[L]\}$ where $L := (x_1, p; x_2, 1-p)$ is a binary lottery with outcomes $x_2 > x_1$ and the expected value $\mathbb{E}[L] := p \cdot x_1 + (1-p) \cdot x_2$. As in Section 4, we assume a linear value function $u(x) = x$.

Using the characterization of binary risks in Lemma 1, a focused thinker's risk premium for the binary lottery L with expected value E, variance V, and skewness S equals

$$r(E, V, S) = \sqrt{Vp(1-p)} \cdot \left(\frac{\Delta^{-g(E-x_1)} - \Delta^{-g(x_2-E)}}{p\Delta^{-g(E-x_1)} + (1-p)\Delta^{-g(x_2-E)}}\right) \tag{6}$$

where outcomes $x_k = x_k(E, V, S)$, $k \in \{1, 2\}$, and probability $p = p(S)$ are defined in (2). A focused thinker strictly prefers the lottery $L(E, V, S)$ over the safe option E if and only if the lottery's risk premium is strictly negative, or, equivalently, the agent's focus lies on the lottery's upside payoff. We conclude:

Proposition 8 (Skewness preferences)**.** *For any given expected value E and variance V, a focused thinker strictly prefers the lottery $L(E, V, S)$ over its expected value E if and only if $S > 0$.*

Proof. It is straightforward to show that a focused thinker's risk premium is strictly negative if and only if $g(x_2 - E) > g(E - x_1)$; that is, her focus lies on the lottery's upside payoff. As g is a strictly increasing function, this is the case if and only if

$$\sqrt{V}\sqrt{\frac{p}{1-p}} = x_2 - E > E - x_1 = \sqrt{V}\sqrt{\frac{1-p}{p}},$$

or equivalently, $p > 1/2$. Then, from equation (1), we conclude that a focused thinker strictly prefers the lottery over its expected value if and only if $S > 0$. $\square$

Hence, a focused thinker seeks right-skewed but avoids left-skewed risks.[16,17] Similar to the salience model, we observe that a focused thinker's preference for right-skewed and aversion toward left-skewed risks is enhanced if the contrast effect becomes stronger.

Definition 6. *We say that the contrast effect is stronger for focusing function g than for focusing function $\hat{g}$ if the difference $g(x) - \hat{g}(x)$ is increasing in $x \in \mathbb{R}_+$.*

Note that the argument of the focusing function represents the difference in values assigned to the outcomes that are feasible in a given state. Thus, the preceding definition of the strength of the contrast effect is analogous to the definition given for the salience model. We conclude:

Proposition 9 (Contrast and skewness preferences)**.** *Let the contrast effect be stronger for focusing function g than for focusing function $\hat{g}$. Then, a focused thinker's risk premium $r(E, V, S)$ is larger for g than for $\hat{g}$ if and only if $S < 0$, that is, the lottery is left-skewed.*

Proof. Analogous to the proof of Proposition 4. $\square$

Puzzles on skewness preferences. Similar to salience theory of choice under risk, the focusing approach yields more reasonable predictions on the magnitude of skewness preferences than cumulative prospect theory. We will show that the puzzles on skewness preferences in the small (Ebert and Strack, 2015, 2016) and in the large (Rieger and Wang, 2006; Azevedo and Gottlieb, 2012) arising for CPT agents can be resolved for focused thinkers.

First, we argue that focusing does not necessarily yield the same unrealistic predictions on skewness preferences in the small as cumulative prospect theory (Ebert and Strack, 2015). Formally, suppose that a focused thinker faces some choice set $\{L, \mathbb{E}[L]\}$. In line with Section 5, let $x_2 > x_1 \geq 0$ and assume that the decision-maker's value from money is strictly increasing and strictly concave, that is, $u'(\cdot) > 0$ and $u''(\cdot) < 0$. As before, we normalize $u(0) = 0$. Then, a focused thinker strictly prefers the risky lottery L over the safe option $\mathbb{E}[L]$ if and only if

$$\frac{u(x_2) - u(\mathbb{E}[L])}{u(\mathbb{E}[L]) - u(x_1)} \cdot \frac{1-p}{p} > \frac{\Delta_1}{\Delta_2},$$

where $\Delta_k := \Delta^{-g(|u(x_k) - u(\mathbb{E}[L])|)}$, $k \in \{1, 2\}$. For any given expected value $E = \mathbb{E}[L]$,

[16] Note that, for any expected value E and variance V, a *relative thinker* (Bushong *et al.*, 2016, see also footnote 12) prefers the binary lottery $L(E, V, S)$ over its expected value E if and only if $S < 0$. It is straightforward to show that, for a relative thinker, we have $g(x_2 - E) > g(E - x_1)$ if and only if $p < 1/2$ as g is strictly decreasing by assumption. Hence a relative thinker seeks left-skewed but avoids right-skewed risks.

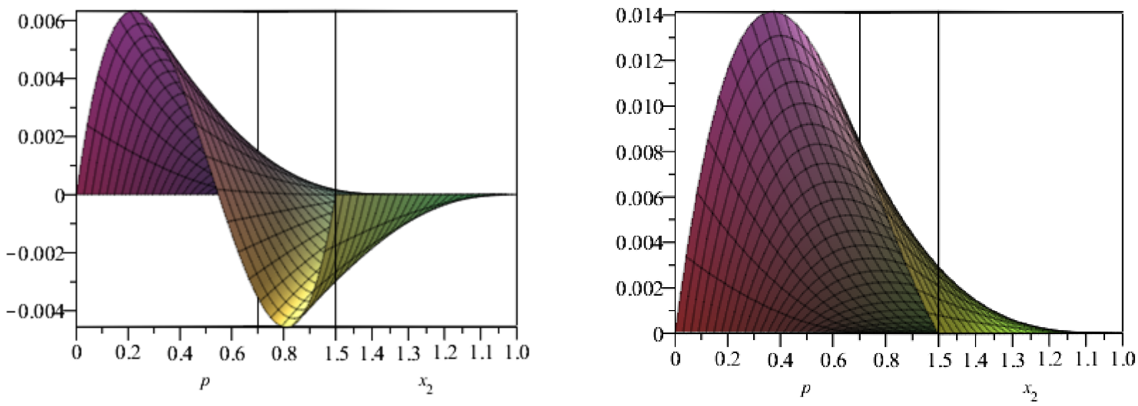
[17] In contrast to the salience model, focusing predicts that the risk premium is independent of the lottery's expected value E (using (2) and equation (6) this result follows immediately).

substituting $p = (x_2 - E)/(x_2 - x_1)$ yields

$$\frac{\frac{u(x_2)-u(E)}{x_2-E}}{\frac{u(E)-u(x_1)}{E-x_1}} > \frac{\Delta_1}{\Delta_2}. \tag{C.1–Focus}$$

Using the following two examples, we show that depending on the value function's curvature there might not exist a binary lottery satisfying condition (C.1–Focus). As in Section 5, we assume power utility $u(x) = x^{\alpha}$ for some $\alpha \in (0,1)$. Furthermore, we consider the focusing function $g(x) = 1 - \frac{1}{1+\gamma x}$ for some $\gamma > 0$ and $x \in \mathbb{R}_+$. Let $\Delta = 0.7$.

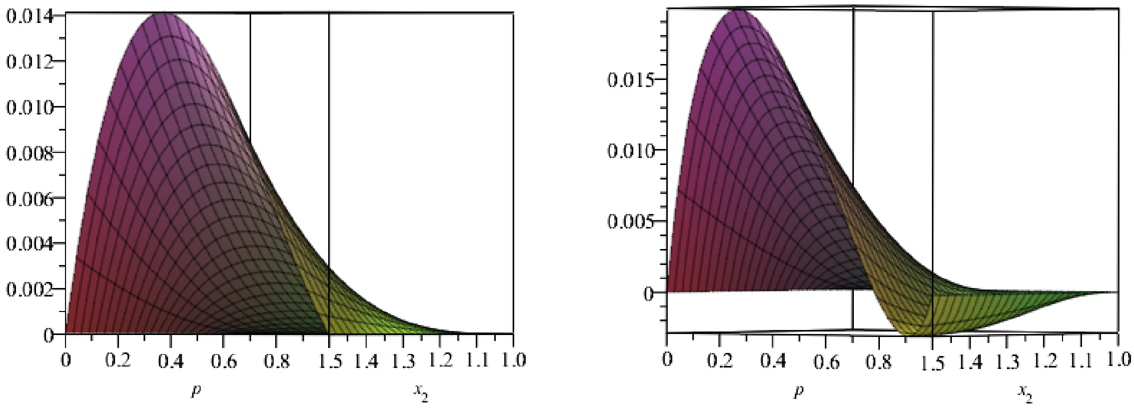
Example 7 (Value function). Assume $\gamma = 1$ so that the focusing function is given by $g(x) = 1 - \frac{1}{1+x}$. If the value function's curvature increases, that is, the parameter α decreases, we observe that inequality (C.1–Focus) is less likely to hold. More specifically, numerical computations show that there exists some threshold value $\tilde{\alpha} \in (0,1)$ such that for any $\alpha \in (0, \tilde{\alpha})$ no unfair, attractive gamble exists. For $\alpha = 0.95$ and $\alpha = 0.5$, Figure 3 illustrates the risk premium r as a function of probability p and upside payoff x_2 for a given downside payoff $x_1 = 1$.



Risk premium for $\alpha = 0.95$. *Risk premium for* $\alpha = 0.5$.

Figure 3: *The above graphs show the risk premium as a function of the upside payoff* x_2 *and the probability* p *that the downside payoff* x_1 *is realized. For* $\alpha = 0.95$*, the risk premium becomes negative for highly right-skewed lotteries (i.e., a large probability* p *on the downside payoff* x_1*) with a large upside payoff* x_2*. For* $\alpha = 0.5$*, the risk premium is non-negative for any feasible lottery.*

Example 8 (Focusing function). Fix $\alpha = 1/2$ so that the value function is $u(x) = \sqrt{x}$. We observe that inequality (C.1–Focus) is more likely to hold for at least some binary lottery L if parameter γ increases, that is, the contrast effect becomes stronger. In fact, numerical computations show that there exists some $\hat{\gamma} > 1$ such that for any $\gamma > \hat{\gamma}$ at least one unfair, attractive gamble exists. For $\gamma = 1$ and $\gamma = 10$, Figure 4 illustrates the risk premium r as a function of probability p and upside payoff x_2 for a given downside payoff $x_1 = 1$.



Risk premium for $\gamma = 1$. *Risk premium for $\gamma = 10$.*

Figure 4: *The above graphs show the risk premium as a function of the upside payoff x_2 and the probability p that the downside payoff x_1 is realized. For $\gamma = 10$, the risk premium becomes negative for highly right-skewed lotteries (i.e., a large probability p on the downside payoff x_1) with a large upside payoff x_2. For $\gamma = 1$, the risk premium is non-negative for any feasible lottery.*

Second, we show that a focused thinker's valuation for binary lotteries with a given expected value $E < \infty$ is bounded. Hence, cumulative prospect theory's predictions on skewness preferences in the large—as delineated by Rieger and Wang (2006) and Azevedo and Gottlieb (2012)—can be resolved in the focusing model.

Proposition 10. *Let $\mathcal{L}(E)$ denote the set of binary lotteries L with finite expected value $E \in \mathbb{R}$. A focused thinker's valuation for some $L \in \mathcal{L}(E)$ is bounded by a function which is affine in E.*

Proof. Since the focusing function is bounded there exists some threshold value $\tilde{\Delta} < \infty$ such that $\Delta^{-g(x)} < \tilde{\Delta}$ for any $x \in \mathbb{R}_+$. The remainder of the proof is analogous to the proof of Proposition 6. □

Appendix C: Mao's lotteries and skewness preferences

Suppose choice set $C := \{L_x, L_y\}$ where $L_x := (x_1, p; x_2, 1-p)$ and $L_y := (y_1, q; y_2, 1-q)$ with outcomes $x_2 > x_1$ and $y_2 > y_1$ and probabilities $p, q \in (0,1)$. As in Section 4, we assume a linear value function $u(x) = x$. Mao (1970) introduced the following class of binary lotteries that allow us to identify skewness preferences.

Definition 7. *Let $p \in \left(0, \frac{1}{2}\right)$. Two perfectly correlated, binary lotteries $L_x := (x_1, p; x_2, 1-p)$ and $L_y := (y_1, 1-p; y_2, p)$ denote a* Mao pair *if both have the same expected value and variance.*

Mao lotteries differ only in their skewness: L_x is left-skewed as its high payoff x_2 occurs with a high probability while lottery L_y is right-skewed as its high payoff y_2 occurs with a small probability (for a formal proof see Ebert and Wiesen, 2011). In line with Definition 3, Ebert and Wiesen (2011) state that "an individual is said to be *skewness seeking* if, for any given Mao pair, she prefers L_y over L_x."

Proposition 11. *For any given Mao pair, a salient thinker prefers L_y over L_x.*

Proof. Due to the perfect correlation of the lotteries, the state space S comprises only two states, that is, $S = \{(x_1, y_2), (x_2, y_1)\}$. Hence a salient thinker prefers the right-skewed lottery L_y over the left-skewed lottery L_x if and only if

$$U^s(L_y) - U^s(L_x) = p(y_2 - x_1)\Delta^{-\sigma(x_1,y_2)} + (1-p)(y_1 - x_2)\Delta^{-\sigma(x_2,y_1)} > 0.$$

Since $p(y_2 - x_1) = -(1-p)(y_1 - x_2) > 0$ by definition—remember that both lotteries have the same expected values—the above inequality simplifies to $\sigma(x_1, y_2) > \sigma(x_2, y_1)$. As $p < 1/2$ by Definition 7, Lemma 1 yields

$$x_1 < y_1 < x_2 < y_2.$$

Thus, ordering implies $\sigma(x_1, y_2) > \sigma(x_2, y_1)$, which was to be proven. □

Finally, it is straightforward to see from the proof above that also a focused thinker prefers L_y over L_x for any given Mao pair. In contrast, a relative thinker in the spirit of Bushong *et al.* (2016) would choose L_x over L_y for any given Mao pair.

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