Evidence for Multiple Strategies in Choice under Risk*

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Abstract

This paper describes an experimental study that yields evidence for the coexistence of two decision strategies of choice under risk. Under the first strategy, choices are made based on aspiration levels – a heuristic that simplifies risky decisions. Under the second strategy, which can be used when aspiration levels are not determinative, choices are made based on preferences for positive skewness. Our model fitting confirms the efficacy of a two-pronged approach that can marshal either strategy depending on specific features of the risky prospects under consideration.

Keywords: aspiration levels, skewness preference, cumulative prospect theory, multiple strategies, decision under risk

JEL: C52, C91, D81

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1 Introduction

In this paper we report on results of an experiment that focuses on multiple strategies of choice in decision making under risk. In this domain, the most popular models of choice are the *normative* expected utility (EU) model (von Neumann & Morgenstern 1947) and the *descriptive* cumulative prospect theory (CPT) model (Tversky & Kahneman 1992). The latter has a mathematical foundation and has received extensive empirical analysis (for a review, see Wakker 2010). According to the terminology of Venkatraman et al. (2014), these theories are "compensatory" in that they evaluate prospects as the sum of the utility of outcomes – as weighted either by probabilities (EU) or decision weights (CPT).

Beginning with the seminal contribution of Simon (1955), an alternative stream of research has emphasized the role of aspiration levels in decisions under risk; much subsequent work (e.g., Payne et al. 1980; Lopes 1987; Lopes & Oden 1999) has yielded data that support the relevance of aspiration levels, and of the overall probability of winning, for risky choice. Decisions based on aspiration levels are "simplifying" strategies (Venkatraman et al. 2014) that allow one to reduce a decision problem's complexity (Payne et al. 1980, Payne 2005). Thus individuals aspire to "satisficing" values (Simon 1956) rather than – as in compensatory theories – optimal values. Diecidue and van de Ven (2008) introduced a model that includes aspiration levels within an expected utility framework, a "hybrid" model incorporating both compensatory (EU) and simplifying (aspiration level) strategies.[1] In addition, several experimental investigations seem to confirm that aspiration levels and overall success probabilities affect decisions made under risk (Payne et al. 1980; Lopes 1987; Lopes & Oden 1999; Payne 2005; Venkatraman

[1]Such hybrid models were defended by Erev et al. (2015). In their competition of choice models, the best-fitting ones are those that include both expected value (the most basic compensatory model) and simplifying heuristics (e.g., tie-breaking rules).

et al. 2009; Venkatraman et al. 2014). However, Diecidue et al. (2015) found no evidence of zero aspiration levels (which most of the literature assumes to exist) and did report evidence of heterogeneity in aspiration levels. Their aggregate data supported CPT, a compensatory approach.

It is therefore clearly desirable to test for whether or not individuals do sometimes "aspire" to a zero outcome and also for whether both simplifying and compensatory decision strategies can coexist in practice. With regard to compensatory strategies, our focus is on skewness preferences and their relation to CPT. A decision strategy based on preference for positive skewness is well modeled by CPT through its probability weighting functions, and empirically derived CPT parameters are compatible with a preference for positive skewness (Spiliopoulos & Hertwig 2015; see also Astebro et al. 2014; Ebert 2015; Ebert & Strack 2015, Thm. 1). Decision makers (DMs) with positive skewness preferences opt for the prospect that could achieve *extreme* positive outcomes.[2] Although skewness preferences are often discussed in finance,[3] they remain relatively unexplored in individual decision making under risk.[4] Grossman and Eckel (2015) reported that nearly 90% of their

[2]So while a positive (or right) preference for skewness describes attraction to a small chance of a large *gain*, a negative (or left) preference describes attraction to a small chance of a large *loss*.

[3]Skewness preferences as the moments of distributions were explored by Golec and Tamarkin (1998), Garrett and Sobel (1999), and Forrest et al. (2002), among others. In financial decisions, preferences for skewness have been documented by Blume and Friend (1975) and by Kraus and Litzenberger (1976). For a more recent study and discussion, see Brünner et al. (2011).

[4]Exceptions include Ebert and Wiesen (2011), who examined the mathematical foundations of skewness in decision theory, as well as Deck and Schlesinger (2010), who found evidence of positive-skewness seeking. The proportion of choices reflecting that tendency was 77% in Ebert and Wiesen (2011) and 64% in Ebert (2015). Wu et al. (2011) used functional magnetic resonance imaging to investigate the neural correlates of skewness preferences in financial decision making, and Symmonds et al. (2011) used fMRI to explore the neuronal sensitivity to skewness in risky choices.

experimental subjects were classified as positive skewness seeking; of these, more than a third took increased risks because of their preference for skewness. Similarly, Astebro et al. (2014) showed that DMs make riskier choices when prospects have positive skewness. The authors explain this finding via the ability of skewness to capture both optimism and "likelihood insensitivity", behavioral patterns characteristic of risky choices and well modeled under CPT by overweighting the small probabilities of large outcomes. Yet to the best of our knowledge, no study has addressed the possibility of decision strategies incorporating skewness *and* aspiration levels.

Our experimental study has two goals, of which the first is to disentangle decision strategies based on aspiration levels from those based on skewness preferences. For that purpose, we use a large set of prospects with several features such that aspiration levels are predictive of choices in some conditions but not in others. When aspiration levels are predictive, the resulting choice patterns characterize a heuristic for reducing the complexity of risky decisions; when those levels are not predictive, we test for whether choices can be explained by skewness preferences. We also investigate what role (if any) is played by the zero outcome – for instance, in contexts where zero might be viewed as a winning opportunity. Our second goal is to compare the fit of the most popular models of risky choices (EU and CPT) and, for the first time, to compare these models when augmented by aspiration levels. To prepare for these undertakings, we designed conditions for testing the existence of preference *reversals* driven by the overall probability of winning (cf. Payne et al. 1980).

We document that subjects employ multiple strategies of choice, either simplifying or compensatory, depending on the type of lottery involved. Our model-fitting exercise corroborates these results by showing that – when choices are driven by aspiration levels – CPT is unable to accommodate our empirical evidence and the best-fitting model is one that incorporates both expected utility and aspiration levels (Diecidue & van de Ven 2008). When choices are instead driven by a preference for positive skewness, it turns out that CPT is the best-fitting model. Thus we offer new insights on the limits of compensatory strategies (e.g., EU and CPT) while identifying circumstances under which simplifying strategies are more likely to be undertaken.

The paper proceeds as follows. In Section 2 we describe the experiment, whose results are reported in Section 3. In Section 4 we fit our experimental data to theoretical models of choice under risk. Our findings are discussed in Section 5, and Section 6 concludes.

2 Experiment

2.1 Participants

Our experiment was conducted at the University of Trento, Italy. Altogether, 49 subjects (22 females and 27 males; mean age = 24 years) took part in the experiment. Each subject received a participation fee plus an amount determined by their performance on one (randomly selected) trial. The experiment was computer based, and the experimental conditions were presented in a random fashion. Instructions were given at the beginning of each experimental session. Our study was approved by the local committee on research ethics.

2.2 Design

The experiment consisted of 168 choices, without feedback, between pairs of three-outcome prospects having the same expected value but different probabilities of winning and losing. We believe that such multi-outcome mixed prospects are ideally suited for testing models of choice that rely on aspiration levels and skewness.[5] Spiliopoulos and Hertwig (2015) considered three-outcome prospects to be significantly more informative than two-outcome prospects, and Diecidue et al. (2015) found no difference (in terms of aspiration levels) when considering prospects with *more* than three outcomes. For these reasons – and given our desire to explore aspiration levels and skewness both – we restricted our attention to cases involving three possible (monetary) outcomes. An example of the stimuli used is pictured in Figure 3 (see Appendix). The 168 trials were clustered into 16 conditions or *lotteries*, L1, . . . , L16.[6]

Conditions L1, L2, and L3 were designed to replicate Payne et al.'s (1980) test for the existence of preference reversals. In the first condition (L1), the two mixed prospects, A and B, have the same expected value but have different probabilities of winning and losing. In L2, the paired three-outcome prospects of L1 were *reduced* by €30 while in L3 all the outcomes of L1 were *increased* by €30.

Conditions L4–L15, the core of our experiment, were designed to test for the presence of aspiration levels and skewness preferences as well as for the contextual role of the zero outcome. In each of conditions L4–L9 there are two cases: achieving aspiration levels is possible with (a) either prospect or (b) only one of the prospects. There are similarly two possible cases in each of conditions L10–L15: achieving aspiration levels could be guaranteed by (a) either prospect or (b) only one of them. Note that conditions L4, L5, L10, and L11 each have one prospect whose payoff is equal to zero. In these conditions it might be possible to predict choices depending on the contextual role of zero – that is, whether zero is evaluated positively or instead negatively.

This experimental design enabled us to identify situations in which choices

[5]Ebert (2015) showed that skewness preferences can be identified from the response of subjects to binary prospects.

[6]These conditions are detailed in Table 6 of the Appendix.

are explained by aspiration levels. Indeed, in conditions where *only one* prospect makes achieving aspiration levels possible (or certain), the expectation is that subjects will choose the prospect that enables reaching their respective aspiration levels. That choice pattern would be reflective of a simplifying strategy. In conditions under which aspiration levels do not predict subjects' choices, we expected DMs to prefer – as would result from a compensatory strategy – the prospect with the highest level of skewness.

Finally, L16 is the only condition in which paired prospects have *different* expected values. In this scenario we expect that a DM will opt for the prospect having the highest expected value (as calculated with reference to the prospects' respective values and probabilities).

3 Results

3.1 Preference Reversals

Our analysis of conditions L1, L2, and L3 begins by testing for the existence of preference reversals. Results are presented in Table 1.

	L1 (Basic)	L2 (Basic − €30)	L3 (Basic + €30)
Pr. Choices	0.51	0.37	0.61

Table 1: Proportion of Choices for Prospect B

The table shows that, in L1, the chance that a subject will opt for prospect A or prospect B is practically the same. For condition L3 we added €30 to the outcome of each prospect, which *increased* the overall probability of winning. Our experimental data show that the proportion of choices for prospect B, whose overall probability of winning is equal to 1, increased from 0.51 to 0.61. In contrast, for condition L2 we subtracted €30 from the outcome of each prospect and thus *decreased* the overall probability of winning. As expected, we observe that the proportion of choices for prospect B, which alone has no possibility of winning, declined from 0.51 to 0.37. We performed Wilcoxon signed-rank tests on these three conditions and found all contrasts to be significant: $p < 0.05$ for L1 versus L3, $p < 0.01$ for L1 versus L2, and $p < 0.001$ for L3 versus L2.

3.2 Multiple Strategies: Disentangling Aspiration Levels and Preferences for Skewness

We designed conditions L4–L15 toward the end of distinguishing between choices based on aspiration levels (a simplifying strategy) and choices based on positive skewness (a compensatory strategy).

Our first prediction was that, in conditions where only one of the prospects offers the chance of achieving aspiration levels, subjects would choose that prospect (e.g., prospect B in L9). Hence an even stronger preference should be observed for the prospect that renders the achievement of aspiration levels certain (e.g., A in L13). Our second prediction was that – in L4, L5, L10, and L11 – the zero outcome is considered positive or negative depending on the value of other outcomes in the same condition. For instance, a preference for prospect A in L4 (resp., in L10) suggests that zero is perceived as a positive (resp., negative) outcome. Our third prediction was that, in conditions under which choices are *not* explained by aspiration level (i.e., L7, L8, L12, L15), those choices can be explained by a preference for positive skewness.

Table 2 reports, for each of conditions L4–L14, the proportion of choices made for prospect A and prospect B. Under conditions such that choices could be pre-

Cond	Choices A	Choices B	Predictability	Cond	Choices A	Choices B	Predictability
L4	0.58	0.42	**Pos***	L5	0.40	0.60	**Neg****
L6	0.53	0.47	AL	L7	0.43	0.57	-
L8	0.44	0.56	-	L9	0.35	0.65	**AL*****
L10	0.28	0.72	**Neg*****	L11	0.66	0.34	**Pos****
L12	0.44	0.56	-	L13	0.80	0.20	**ALc*****
L14	0.36	0.64	**ALc*****	L15	0.46	0.54	-

Table 2: Proportion and Predictability of Choices.

Notes: Under "Predictability" we indicate whether the observed choices are explained by aspiration levels (AL) or by aspiration certainty (ALc) and whether the zero outcome is perceived as positive (Pos.) or negative (Neg.). Boldface is used to report significant differences in choice proportions.

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

dicted solely by aspiration levels (with or without certainty) or by the subjective perception of zero (as a positive or negative outcome), that prediction is reported in the "Predictability" column(s). We next discuss the reported values in more detail.

- In condition L4, prospect A has one zero outcome and two negative outcomes while prospect B's outcomes are all negative (see Table 6 in the Appendix). Here a subject's choice of prospect could depend on whether the zero outcome is perceived as positive or rather as negative. Although in L4 we observe a preference for A, in L5 we observe a preference for B – the only prospect with a positive outcome. This result suggests that subjects view the zero outcome as positive in condition L4 but as negative in L5.

- In condition L6 we expected a preference for A, the only prospect providing a chance to achieve an aspiration level (i.e., 2). We do observe that preference, but it is not *significantly* stronger than the preference observed for prospect B. In L7, where both prospects offer the possibility of achieving aspiration levels, the actual choices cannot be explained by those aspiration levels.

- In condition L8, all the values (for both prospects) are negative. Because aspiration levels cannot be reached in this condition, it could be that choices reflect a preference for skewness. In L9, only prospect B offers a positive outcome and, as expected, we observe that preference.

- In condition L10, prospect A has one zero outcome and two positive outcomes while all three of prospect B's outcome values are positive. Here, as in L4, subjects' choices might vary depending on how the zero outcome is perceived. In this condition we observed a clear preference for prospect B. In L11, again prospect A has one zero and two positive outcomes but now prospect B has one negative value (-50). Here, as expected, subjects opted for prospect A.

- In condition L12, both prospects offer the certainty of achieving aspiration levels (since all values of both prospects are positive). Just as in conditions L8, L7, and L15, choices in L12 are not explained by aspiration levels. In condition L13, only prospect A gives the *certainty* with regard to achieving aspiration levels. As aspiration levels would predict, a clear preference is observed for A in this condition.

- In condition L14, we observed (as expected) a clear preference for B, the prospect that gives the certainty of achieving aspiration levels. In condition L15 both prospects offer the possibility of achieving aspiration levels. The actual choice cannot be explained by aspiration levels; hence we are led to check for skewness preferences.

In short: under conditions L4–L15, our expectations are confirmed when choices can be predicted by aspiration levels alone. In order to identify cases in which aspiration levels and skewness preferences could each be accounting for the observed choices (as when DMs choose an aspiration-achieving prospect that is also highly skewed), we ran a regression restricted to the cases where the prospect that satisfies aspiration levels is the one with the *lowest* level of skewness. If choices were explained by the simplifying strategy based on aspiration levels only – rather than by preferences for skewness – then we should observe that the difference in skewness (dSkw) is significant and negative because the aspiration-achieving prospect chosen has the lowest skewness. Indeed, in these particular cases the coefficient for dSkw is significantly negative ($p < 0.001$).

In all other conditions – that is, where aspiration levels are *not* predictive – choices might reflect a compensatory approach based on preferences for skewness. For these conditions we ran a logit regression with the following regressors: the difference between the probabilities of winning (dPrWin) and losing (dPrLoss), the difference in standard deviation (dSD), and the difference in skewness (dSkw). Results are reported in Table 3.

Model 1 of Table 3 refers to conditions L7, L8, L12, and L15 (i.e., conditions under which a simplifiying strategy based on aspiration levels can *not* be undertaken) and shows a significant probability of winning. This model also shows that, in these four conditions, the difference in skewness is significant and positive – thus confirming our prediction that, when aspiration levels are not predictive, choices are driven by a preference for positive skewness. This result accords with findings from previous studies (e.g., Astebro et al. 2014; Ebert 2015; Spiliopoulos & Hertwig 2015) where skewness has been found to play a pivotal role in risky choices.

Model 2 of the table refers to condition L16, which involves prospects of different expected value. The logistic regression reveals that dSD and dEV are the only significant regressors in this condition. Thus we demonstrate that, when a simplified strategy cannot be undertaken, subjects may employ a compensatory

Table 3: Model 1: L7,L8,L12,L15. Model 2: L16

	Model 1	Model 2
	choice	choice
dPrWin	1.686*	
	(2.17)	
dPrLoss	0.634	
	(0.74)	
dSD	-0.00173	-0.0229*
	(-0.78)	(-2.21)
dSkw	0.218***	0.188
	(3.65)	(0.75)
dEV		0.110***
		(3.97)
cons	-0.143	0.0760
	(-1.49)	(0.71)
N	1834	479

Notes: t statistics in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

strategy that relies on (the differences in) expected value and positive skewness.

3.3 Response Times

Figure 1 graphs subjects' response times (in hundredths of a second, cs) under each lottery condition. Although the response times are fairly heterogeneous, we can see that choices are made more rapidly than the overall average in conditions L3, L10, and L13; choices are made more slowly than average in L1, L8, and L16.

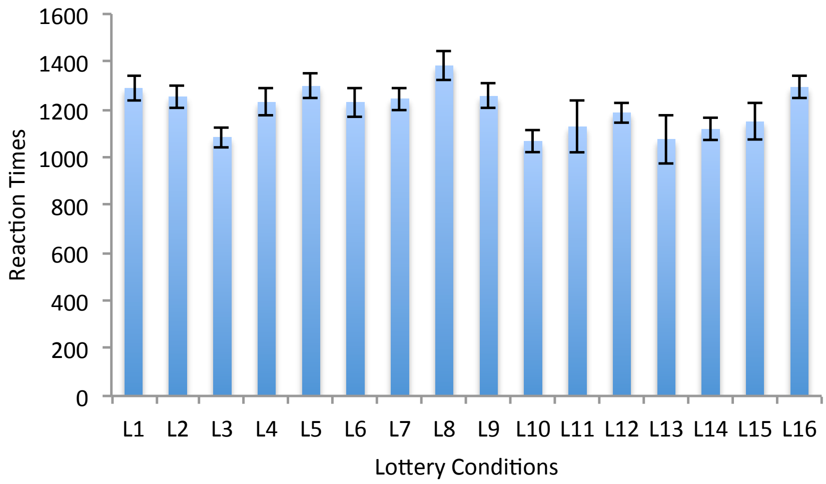

Figure 1: Response Times (cs) in the 16 Tested Conditions

Figure 2 graphs subjects' response times under these two main groups. The difference between the groups is significant ($\chi^2 = 31.92$, $p < 0.001$). In the former trio (L3, L10, L13) we have three conditions under which choices can be explained by a simplified strategy; the latter trio (L1, L8, L16) includes conditions that might call for a more complex decision strategy. We can use these results to argue that choices in the "fast" group of conditions are made using a simplifying strategy that is not mentally taxing, whereas choices in the "slow" group are instead made using a compensatory strategy that entails a greater cognitive load.

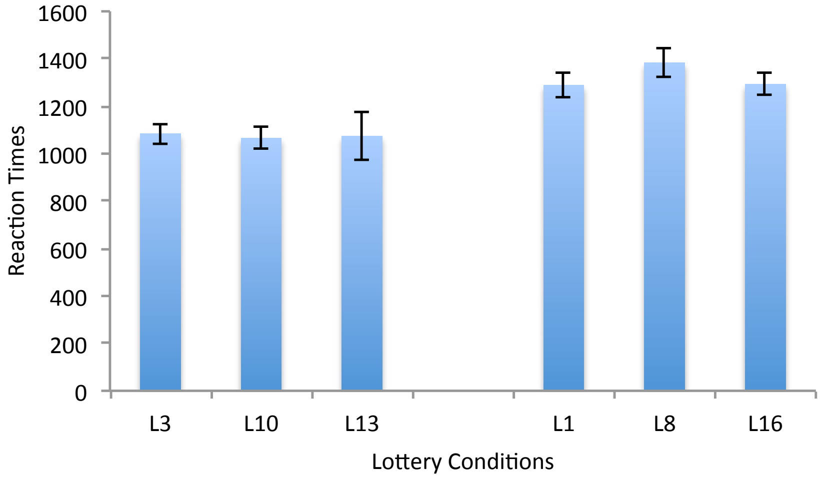

Figure 2: Response Times (cs) in two Groups of Conditions

4 Model Fitting

In addition to the analyses just described, we also performed a maximum likelihood estimation (MLE) in order to see how well the most popular models of decision making under risk fit subjects' actual choices.[7] These models include expected utility and cumulative prospective theory as well as their hybrid versions, EU with aspiration levels (EU&AL) and CPT with aspiration levels (CPT&AL). To the best of our knowledge, no previously published analysis is based on MLE of models that incorporate aspiration levels. In this approach, for each utility model we choose a range of relevant parameter values. Then, in light of the observed choices, we computed the likelihood (transformed by the natural logarithm) and adjusted the estimated parameters so as to *maximize* the log-likelihood.

[7]Other studies that address model fitting include Tversky and Kahneman (1992), Camerer and Ho (1994), Gonzalez and Wu (1999), Abdellaoui et al. (2005), and Stott (2006).

Expected Utility

Consider prospect $X = (p_1, x_1; \ldots; p_n, x_n)$ yielding outcome x_j with probability p_j, $j = 1, \ldots, n$. Probabilities are nonnegative and sum to 1. We take an EU model with a power function $U(x_j) = x_j^\alpha$, in which case the value of prospect X is defined as $V(X) = \sum_{j=1}^n p_j \times U(x_j)$. The logistic choice function between two lotteries is now defined by $F(V) = 1/(1 + \exp\{-\varepsilon(V_1 - V_2)\})$. The conditional log-likelihood can therefore be written as

$$\begin{aligned} \ln L^{\mathrm{EU}}(\alpha; y, X) &= \sum_i \ln l_i^{\mathrm{EU}} \\ &= \sum_i [y_i \ln F(V) + (1 - y_i) \ln(1 - F(V))]. \end{aligned} \tag{1}$$

Here (and throughout), $y_i = 1$ or 0 according as whether – in trial i – the DM chose prospect A or prospect B.

Expected Utility & Aspiration Levels

In Diecidue and van de Ven (2008), the decision maker's preferences are expressed as a combination of expected utility and the aspiration level. For the prospect X, then, $P(x^+)$ denotes the overall probability of *winning* while $P(x^-)$ denotes the overall probability of *losing*; the parameters μ^+ and λ^- measure the effect of aspiration success and of aspiration failure, respectively. Hence the valuation of a prospect X with outcomes x_j $(j = 1, \ldots, n)$ and probability p_j $(j = 1, \ldots, n)$ can be expressed as

$$X \mapsto V(X) = \sum_{j=1}^n p_j u(x_j) + \mu^+ P(x^+) - \lambda^- P(x^-), \quad \mu^+, \lambda^- \in \mathbb{R}^+.$$

The conditional log-likelihood under this theoretical model is therefore

$$\begin{aligned}\ln L^{\text{EU\&AL}}(\alpha, \mu^+, \lambda^-; y, X) &= \sum_i \ln l_i^{\text{EU\&AL}} \\ &= \sum_i [y_i \ln F(V) + (1 - y_i) \ln(1 - F(V))], \qquad (2)\end{aligned}$$

where again $y_i = 1$ or 0 according as whether, in trial i, the DM chose prospect A or prospect B. For this model, we must estimate three parameters: the utility function's α as well as μ^+ and λ^-.

Cumulative Prospect Theory

We also checked to see how well CPT (Tversky & Kahneman 1992) predicts our subjects' choices. Under this model, the value of prospect X is defined as $V(I) = \sum_{j=1}^{n} U(x_j) \times \pi_j$; here the utility function $U(x_j) = x^\alpha$ if $x \geq 0$ or $U(x_j) = -\lambda(-x)^\beta$ if $x < 0$. Thus the parameters α and β reflect the utility function's curvature in the case of (respectively) gains and losses, and λ is the loss aversion parameter. Finally, the π_j are decision weights derived from the outcome probability:

$$\begin{aligned}\pi_n^+ &= w^+(p_n), \qquad \pi_{-m}^- = w^-(p_{-m}); \\ \pi_j^+ &= w^+(p_j + \cdots + p_n) - w^+(p_{j+1} + \cdots + p_n), \quad 0 \leq j \leq n-1; \\ \pi_j^- &= w^-(p_{-m} + \cdots + p_j) - w^-(p_{-m} + \cdots + p_{j-1}), \quad 1 - m \leq j \leq 0.\end{aligned}$$

We employed Prelec's (1998) two-parameter weighting function, $w(p) = \exp\{-\delta(-\ln p)^\gamma\}$.

The conditional log-likelihood under cumulative prospect theory is

$$\begin{aligned}&\ln L^{\text{CPT}}(\alpha, \beta, \lambda, \delta^+, \gamma^+, \delta^-, \gamma^-; y, X) \\ &\quad = \sum_i \ln l_i^{\text{CPT}} = \sum_i [y_i \ln F(V) + (1 - y_i) \ln(1 - F(V))]; \qquad (3)\end{aligned}$$

as before, $y_i = 1$ (resp., $y_i = 0$) means that, in trial i, the DM chose prospect A or prospect B.This model requires that we estimate seven parameters.

Cumulative Prospect Theory & Aspiration Levels

The fourth tested model integrates cumulative prospect theory with aspiration levels. Here the value of prospect X is defined as

$$V(X) = \sum_{j=1}^{n} U(x_j) \times \pi_j + \mu^+ w(P(x^+)) - \lambda^- w(P(x^-)),$$

where $U(x_j) = x^\alpha$ if $x \geq 0$ or $U(x_j) = -\lambda(-x)^\beta$ if $x < 0$. Just as under CPT, the probability weighting function is $w(p) = \exp\{-\delta(-\ln p)^\gamma\}$.

Hence the conditional log-likelihood for this model specification is

$$\begin{aligned} &\ln L^{\text{CPT\&AL}}(\alpha, \beta, \lambda, \delta^+, \gamma^+, \delta^-, \gamma^-, \mu^+, \lambda^-; y, X) \\ &\quad = \sum_i \ln l_i^{\text{CPT\&AL}} = \sum_i [y_i \ln F(V) + (1 - y_i) \ln(1 - F(V))]; \end{aligned} \tag{4}$$

once again, $y_i = 1$ (resp., $y_i = 0$) means that, in trial i, the DM chose the prospect A or prospect B. in total, there are nine parameters to estimate.

MLE Results

We divided our analysis of conditions L4–L15 into two groups. For the conditions in which choices can be explained by a simplifying strategy based on aspiration levels, Table 4 reports the estimated parameters. In the last two rows we report the log-likelihood and the Akaike information criterion (AIC) in order to identify the best-fitting model. The AIC is an adjusted measure of model selection: AIC $= -2 \ln L + 2k$ for k the number of model parameters, where a *lower* AIC value indicates a better fit.

The analysis reveals that incorporating aspiration levels improves the EU model's fit and that the model of Diecidue and van de Ven (2008), with an AIC value of 99.789, is the best-fitting for this group of conditions – in line with our prediction of a simplifying strategy. The two models that incorporate AL allow us

Parameter	EU	EU&AL	CPT	CPT&AL
α	0.961	0.961	0.207	0.173
β	—	—	0.334	0.391
λ	—	—	1.531	1.204
δ^+	—	—	0.882	0.913
γ^+	—	—	0.697	0.613
δ^-	—	—	1.314	1.409
γ^-	—	—	0.430	0.601
μ^+	—	1.878	—	0.579
λ^-	—	1.100	—	1.005
Log-likelihood	-50.723	-46.895	-46.164	-44.670
AIC	103.445	99.789	106.328	107.340

Table 4: MLE Parameters When Aspiration Levels *Do* Determine Choices

to measure, for the first time, μ^+ and λ^-. These parameters were introduced in the aspirations-based model of Diecidue and van de Ven implying that the utility function is discontinuous and jumps at zero. The estimated values of μ^+ and λ^- suggest the existence of both a positive and a negative jump at zero owing to the effect of aspiration levels on the evaluation of success or failure.

Table 5 reports the estimated parameters for the group of conditions under which an AL-based simplifying strategy is *not* predictive of subjects' choices. For these lotteries, the model that best captures the underlying decision strategy is CPT. An AIC value of 60.222 is estimated for this strategy, which underscores the descriptive power of CPT for choices that are driven by a compensatory decision strategy.

Parameter	EU	EU&AL	CPT	CPT&AL
α	0.955	0.806	0.350	0.350
β	—	—	0.439	0.464
λ	—	—	1.737	1.596
δ^+	—	—	1.006	1.040
γ^+	—	—	0.722	0.729
δ^-	—	—	1.231	1.271
γ^-	—	—	0.627	0.671
μ^+	—	1.179	—	1.982
λ^-	—	0.621	—	0.556
Log-likelihood	−40.200	−37.815	−23.111	−23.029
AIC	82.399	81.629	60.222	64.058

Table 5: MLE Parameters When Aspiration Levels *Do Not* Determine Choices

5 Discussion

We used a variety of conditions, involving choices with prospects of the same expected value, to detect the coexistence of simplifying and compensatory strategies in choices under risk. Conditions L1, L2, and L3 were used to test for preference reversals, as first reported by Payne et al. (1980), that reflect the overall probabilities of winning and losing.

We replicated evidence for preference reversals after a negative (L2) or positive (L3) translation. This behavioral pattern is a heuristic used in decision making under risk that links choices to aspiration levels and to the probability of winning (Payne et al. 1980; Lopes 1987; Lopes & Oden 1999; Payne 2005; Diecidue & van de Ven 2008; Venkatraman et al. 2014). The overall probability of winning might also affect perceptions of a prospect's "salience", which is another important component of choice under risk (Bordalo et al. 2012).

Conditions L4–L15 constitute the core of our study. These conditions were designed to disentangle multiple decision strategies in addition to subjects' context-dependent evaluations of the zero outcome. The conditions also allowed us to identify and explain when simplifying strategies (based on aspiration levels) or compensatory strategies (based on skewness preferences) are in play. We discovered that decision makers opt for a prospect if it is the only one offering a chance to achieve aspiration levels; as one might expect, there is also a strong preference for a prospect that entails the *certainty* of achieving aspiration levels. All conditions whose choices are predicted and explained by aspiration levels are illustrated in Table 2. When conditions include a zero outcome, that value is perceived as positive or negative depending on the value of *other* outcomes in the same condition. Our data confirm that subjects clearly prefer (resp., do not prefer) the prospect that includes 0 in L4 (resp., in L10), where zero is (resp., is not) an aspiration level.

In the other conditions (L7, L8, L12, L15), where a simplifying strategy based on aspiration levels cannot be undertaken, we dealt with two different cases: either all six outcomes (three outcomes each in prospect A and B) are negative, as in L8, and so aspiration levels are unattainable; or all the outcomes are positive, as in L12, and so aspiration levels are not determinative of the subject's choice. In the latter group of cases we tested for whether choices were affected by subjects' skewness preferences. We found that the difference in skewness (dSkw) between chosen versus unchosen prospect is significant in all these conditions; this finding suggests that, ceteris paribus, subjects prefer the prospect with the greater positive skewness and with the lesser negative skewness. It seems likely that this preference for skewness captures the decision strategy under risk when the DM is unable to reduce decision complexity via some simplifying strategy (e.g., aspiration levels).

Finally, our third "group" consists only of condition L16, under which the two prospects have a *different* expected value. Recall from Model 2 of Table 3 that, among the regressors we used, the difference in standard deviation (dSD) and the difference in expected value (dEV) had a significant effect on choices. The implication is that, in condition L16, choices are explained (as expected) by differences in expected value.

Response times show that choices are made more rapidly than average in L3, L10, and L13 but are made more slowly than average in L1, L8, and L16. In the "fast" group, the lotteries are such that the choice of prospect (i.e., A versus B) should be easy to make and is well predicted by aspiration levels. The "slow" group comprises the lotteries in which choices cannot rely on a simplifying decision process. It comes as no surprise that choices in the fast group are driven by a simplifying strategy based on aspiration levels – a cognitively undemanding heuristic. In contrast, choices in the slow group are driven by a compensatory strategy that is cognitively more demanding.

According to the maximum likelihood estimation performed in Section 4, the model of Diecidue and van de Ven (2008) fits the observed choices best in all experimental conditions under which choices can be explained by a simplifying approach based on aspiration levels. Yet in the conditions under which the DM cannot undertake a simplifying strategy, the best-fitting model is cumulative prospect theory. This result favoring CPT accords with our previous analysis on preferences for positive skewness. When one considers these two results in tandem – the first in favor of EU&AL and the second in favor of CPT – it becomes evident that a model's descriptive power depends strongly on the context and on the decision process triggered by that context.

6 Conclusion

In this empirical study we first confirmed the existence of preference reversals (as posited by Payne et al. 1980), a result in line with previous findings on aspiration levels and heuristics based on the probability of winning. We then found also that our subjects prefer prospects offering the chance to achieve aspiration levels and, to an even greater extent, prospects that offer the achievement of aspiration levels with certainty. In conditions where a decision strategy cannot rely on aspiration levels, we observe that preferences for positive skewness explain the subjects' choice behavior. The results of our maximum likelihood estimation confirm the co-existence of simplifying, aspirations-based strategies and compensatory, skewness-based strategies – the former as described by Diecidue et al.'s (2008) model and the latter as described by cumulative prospect theory. Our results not only reflect the predictive power of CPT but also identify situations in which that theory *fails* to predict choice.

Overall, our results strongly suggest that the optimal strategy for dealing with risky prospects depends on (inter alia) such factors as structure and complexity of the prospects. Echoing Venkatraman et al.'s (2014) study of decision-making heuristics under complexity and risk, we found that a DM may well employ both a simplifying strategy (based on, e.g., the likelihood of winning or of achieving aspiration levels) and a compensatory strategy (based on, e.g., preferences for positive skewness) depending on the possible outcomes of the prospects in question. Such behavior is evidence of a multiple-strategy approach to decision making.

Appendix

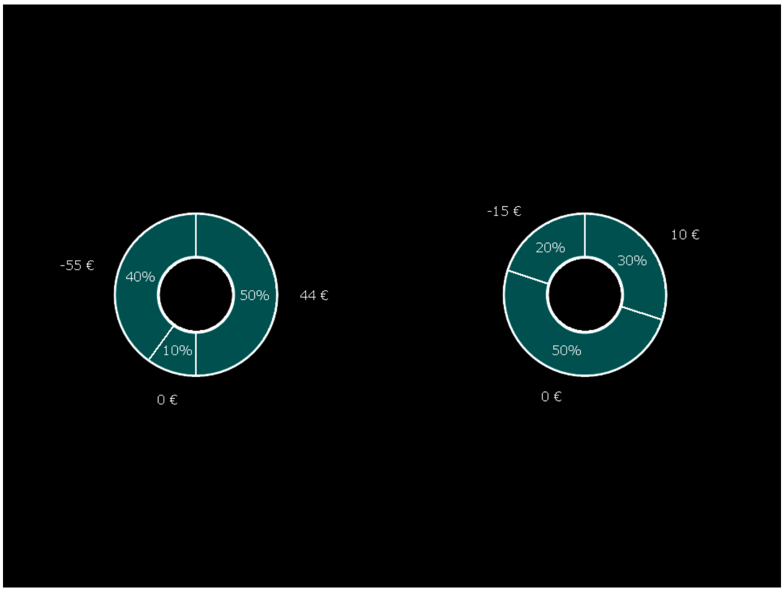

Figure 3: Example Stimulus Presentation: Choice between Two Prospects

	Prospect A			Prospect B		
L1	44	0	–55	10	0	–15
	0.5	0.1	0.4	0.3	0.5	0.2
L2	14	–30	–85	–20	–30	–45
	0.5	0.1	0.4	0.3	0.5	0.2
L3	74	30	–25	40	30	15
	0.5	0.1	0.4	0.3	0.5	0.2
L4	0	–44	–99	–29	–44	–54
	0.5	0.1	0.4	0.2	0.5	0.3
L5	0	–8	–24	8	–8	–16
	0.4	0.4	0.2	0.2	0.4	0.4
L6	2	–58	–94	–50	–58	–74
	0.3	0.2	0.5	0.4	0.4	0.2
L7	2	–10	–40	35	–10	–100
	0.5	0.3	0.2	0.6	0.1	0.3
L8	–2	–62	–98	–54	–62	–78
	0.3	0.2	0.5	0.4	0.4	0.2
L9	–2	–17	–40	6	–17	–32
	0.3	0.5	0.2	0.2	0.5	0.3
L10	25	15	0	30	15	5
	0.3	0.5	0.2	0.2	0.5	0.3
L11	32	20	0	55	20	–50
	0.5	0.2	0.3	0.4	0.4	0.2
L12	101	46	2	56	46	31
	0.4	0.1	0.5	0.3	0.5	0.2
L13	34	22	2	57	22	–48
	0.5	0.2	0.3	0.4	0.4	0.2
L14	94	58	–2	118	58	22
	0.5	0.2	0.3	0.3	0.2	0.5
L15	30	18	–2	53	18	–52
	0.5	0.2	0.3	0.4	0.4	0.2
L16	20	30	40	20	30	40
	0.2	0.35	0.45	0.3	0.3	0.4

Table 6: The 16 Experimental Conditions

Notes: All other pairs of prospects played by subjects have the same qualitative structure but different payoffs. The full list of pairs is available upon request.

References

Abdellaoui, M., Vossmann, F., & Weber, M. (2005). Choice-based elicitation and decomposition of decision weights for gains and losses under uncertainty. *Management Science*, 51(9), 1384-1399.

Astebro, T., Mata, J., & Santos-Pinto, L. (2014). Skewness seeking: risk loving, optimism or overweighting of small probabilities?. *Theory and Decision*, 78(2), 189-208.

Blume, M. E., & Friend, I. (1975). The asset structure of individual portfolios and some implications for utility functions. *Journal of Finance*, 585-603.

Bordalo, P., Gennaioli, N., & Shleifer, A. (2012). Salience Theory of Choice under Risk. *The Quarterly journal of economics*, 127(3), 1243-1285.

Brünner, T., Levínský, R., & Qiu, J. (2011). Preferences for skewness: evidence from a binary choice experiment. *The European Journal of Finance*, 17(7), 525-538.

Camerer, C. F., & Ho, T. H. (1994). Violations of the betweenness axiom and nonlinearity in probability. *Journal of Risk and Uncertainty*, 8(2), 167-196.

Deck, C., & Schlesinger, H. (2010). Exploring higher order risk effects. *The Review of Economic Studies*, 77(4), 1403-1420.

Diecidue, E., Levy, M., & van de Ven, J. (2015). No Aspiration to Win? An Experimental Test of the Aspiration Level Model. *Journal of Risk and Uncertainty*, 51(3), 245-266.

Diecidue, E., & van de Ven, J. (2008). Aspiration level, probability of success and failure, and expected utility. *International Economic Review*, 49(2), 683-700.

Ebert, S. (2015). On skewed risks in economic models and experiments. *Journal of Economic Behavior & Organization*, 112, 85-97.

Ebert, S., & Strack, P. (2015). Until the Bitter End: On Prospect Theory in a

Dynamic Context. *American Economic Review*, 105(4), 1618-33.

Ebert, S., & Wiesen, D. (2011). Testing for prudence and skewness seeking. *Management Science*, 57(7), 1334-1349.

Erev, I., Ert, E., & Plonsky, O. (2015). From Anomalies to Forecasts: A Choice Prediction Competition for Decisions under Risk and Ambiguity. *Mimeo*, 1-56

Forrest, D., Simmons, R., & Chesters, N. (2002). Buying a dream: Alternative models of demand for lotto. *Economic Inquiry*, 40(3), 485-496.

Garrett, T. A., & Sobel, R. S. (1999). Gamblers favor skewness, not risk: Further evidence from United States? lottery games. *Economics Letters*, 63(1), 85-90.

Golec, J., & Tamarkin, M. (1998). Bettors love skewness, not risk, at the horse track. *Journal of Political Economy*, 106(1), 205-225.

Gonzalez, R., & Wu, G. (1999). On the shape of the probability weighting function. *Cognitive Psychology*, 38(1), 129-166.

Grossman, P. J., & Eckel, C. C. (2015). Loving the Long Shot: Risk Taking with Skewed Lotteries.*Journal of Risk and Uncertainty*, 51, 195-217.

Kraus, A., & Litzenberger, R. H. (1976). Skewness preference and the valuation of risk assets. *The Journal of Finance*, 31(4), 1085-1100.

Lopes, L. L. (1987). Between hope and fear: The psychology of risk. *Advances in Experimental Social Psychology*, 20(3), 255-295.

Lopes, L. L., & Oden, G. C. (1999). The role of aspiration level in risky choice: A comparison of cumulative prospect theory and SP/A theory. *Journal of Mathematical Psychology*, 43(2), 286-313.

Payne, J. W. (2005). It is whether you win or lose: The importance of the overall probabilities of winning or losing in risky choice. *Journal of Risk and Uncertainty*, 30(1), 5-19.

Payne, J. W., Laughhunn, D. J., & Crum, R. (1980). Translation of gambles and aspiration level effects in risky choice behavior. *Management Science*, 26(10),1039-1060.

Prelec, D. (1998). The probability weighting function. *Econometrica*, 497-527.

Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics*, 99-118.

Simon, H. A. (1956). Rational choice and the structure of the environment. *Psychological Review*, 63(2), 129.

Spiliopoulos, L., & Hertwig, R. (2015). Nonlinear Decision Weights or Skewness Preference? A Model Competition. *A Model Competition* (August 12, 2015).

Stott, H. P. (2006). Cumulative prospect theory's functional menagerie. *Journal of Risk and Uncertainty*, 32(2), 101-130.

Symmonds, M., Wright, N. D., Bach, D. R., & Dolan, R. J. (2011). Deconstructing risk: separable encoding of variance and skewness in the brain. *Neuroimage*, 58(4), 1139-1149.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, 5(4), 297-323.

Venkatraman, V., Payne, J. W., Bettman, J. R., Luce, M. F., & Huettel, S. A. (2009). Separate neural mechanisms underlie choices and strategic preferences in risky decision making. *Neuron*, 62(4), 593-602.

Venkatraman, V., Payne, J. W., & Huettel, S. A. (2014). An overall probability of winning heuristic for complex risky decisions: Choice and eye fixation evidence. *Organizational Behavior and Human Decision Processes*, 125(2), 73-87.

von Neumann, J., & Morgenstern, O. (1947). Theory of games and economic behavior (2nd ed.).*Princeton, NJ: Princeton University Press.*

Wakker, P. P. (2010). Prospect theory: For risk and ambiguity. *Cambridge University Press.*

Wu, C. C., Bossaerts, P., & Knutson, B. (2011). The affective impact of financial skewness on neural activity and choice. *Plos One*, 6(2), 1-7