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Aspiration Levels and Preference for Skewness in Choice Under Risk

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This paper describes an experiment designed to study the effect of aspiration levels on individual choices under risk. We observe preferences for prospects that offer various probabilities of achieving aspiration levels; the resulting choice patterns characterize a heuristic for reducing the complexity of risky decisions. In cases where aspiration levels are not predictive, choices can be explained by preferences for positive skewness. Our results confirm the efficacy of a two-pronged approach that includes both compensatory and simplifying strategies for choosing among risky prospects. Of the former strategies, cumulative prospect theory best fits our experimental data.

Keywords: Aspiration Levels; Preferences for Skewness; Cumulative Prospect Theory; Multiple Strategy Approach
JEL: C52, C91, D81

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1 Introduction

Two of the most popular theories in individual decision under risk are expected utility (von Neumann & Morgenstern 1947) and cumulative prospect theory (Tversky & Kahneman 1992). Cumulative prospect theory (CPT) was introduced, together with several other theories,[1] to repair the descriptive failures of expected utility (EU) challenged since the introduction of the Allais paradox (1953). Broadly speaking, these two theories are *compensatory* (Venkatraman et al. 2014) in the sense that they evaluate prospects as the sum of the utility of outcomes 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 and a good deal of research (e.g., Payne et al. 1980; Lopes 1987; Lopes & Oden 1999) has yielded data that support the relevance of aspiration levels for risky choice. In particular, Payne et al (1980) was the first paper documenting that preferences among risky lotteries changed depending on the location of an aspiration level and hence showing preference reversals unexplained by either EU or CPT. Decisions based on aspiration levels can be defended as *simplifying* strategies (non-compensatory strategies in the terminology of Venkatraman et al. 2014) that allow decreasing the complexity of a decision problem (Payne et al. 1980, Payne 2005). In this case, individuals aspire to achieve values that are "satisficing" (Simon 1956) rather than optimizing as in the compensatory theories.

Diecidue and van de Ven (2008) introduced a model that include aspiration

[1] Among the several alternatives to expected utility we cite prospect theory (Kahneman & Tversky 1979), regret theory (Loomes & Sugden 1982), disappointment theory (Loomes & Sugden 1986; Gul 1991), prospective reference theory (Viscusi 1989), rank and sign-dependent utility (Luce and Fishburn 1991), and rank-dependent utility (Quiggin 1982). For an exhaustive list and analysis see for example Starmer (2000).

levels in decisions under risk. The model stresses two aspects of decision making. First, decision makers (DMs) do not evaluate risky decisions exclusively by looking at aspiration levels, but also by considering the entire distribution of payoffs. For this reason, the model includes aspiration levels within an expected utility framework, hence originating a 'hybrid' model between compensatory (EU) and simplifying strategy (aspiration level).[2] The second aspect is that the utility function is discontinuous around the outcome zero in order to reflect the impact of a winning or losing outcome. It is worth noting that all winning outcomes are aspiration levels. Several experimental investigations have reported results indicating that aspiration levels and the overall probabilities of winning and losing play a role in decision under risk (Payne et al. 1980; Lopes 1987; Lopes & Oden 1999; Payne 2005; Venkatraman et al. 2009, 2014). Diecidue et al. (2015), did not find evidence of an aspiration level exactly at zero and reported evidence for aspiration levels heterogeneity. Their paper, as a consequence, left a number of unanswered questions. It is not clear, for example, under which conditions the outcome zero serves as an aspiration level or not. It is not clear under which conditions, DMs rely on aspiration-based heuristics and when instead they rely on different processes. Although aspiration levels and the overall probabilities of winning and losing are intuitive and seem to carry relevant explanatory power (Payne 2005, Venkatraman et al. 2014, Erev et al. 2015), still cumulative prospect theory fits the data very well (Diecidue et al. 2015). In this sense an explanation allowing to reconcile aspiration levels, overall probabilities, and CPT is highly called for.

We believe that preference for *skewness* is such an alternative explanation. A positive (or right) preference for skewness entails an attraction towards a small

[2]Hybrid models have been defended recently by Erev et al. (2015). In fact, in their choice competition the best fitting models are those that consider expected value (the most basic compensatory model) and heuristics as simplifying tie-breaking rules.

chance of a large gain, while a negative (or left) preference entails attraction towards a small chance of a large loss. Although quite popular in finance[3] the preferences for skewness are relatively unexplored in individual decision making under risk. Among the works in this domain, Ebert and Wiesen (2011) explored the mathematical foundations of skewness in decision theory, Deck and Schlesinger (2010) found evidence of positive skewness seeking. Ebert (2015) showed that 64% of choices were positive skewness seeking and that this proportion was 77% in Ebert and Wiesen (2011). Grossman and Eckel (2015) reported close to 90% of subjects classified as positive skewness seeking; more than one third of these subjects increase their risk taking as a consequence of their preference for skewness. In a related experimental study, Astebro et al. (2014) showed that DMs make riskier choices when prospects have positive skewness. The authors explain this finding because skewness is able to capture the *optimism* and *likelihood insensitivity* which are two behavioral patterns often found in risky choices (Wakker 2010) and successfully modeled by CPT through the overweighting of small probabilities of large outcomes. In fact, the empirically derived parameters for CPT are compatible with preference for positive skewness (Spiliopoulos and Hertwig 2015). The relation between CPT and skewness is henceforth receiving increasing attention (Astebro et al. 2014, Ebert 2015, Spiliopoulos and Hertwig 2015, Theorem 1 in Ebert and Strack 2015). Importantly, aspiration levels are also naturally related to skewness, with the difference that the former represents a simplifying decisional strategy while the latter a compensatory one. Decision makers (DMs) with preferences for positive skewness opt for the prospect that offers the possibil-

[3]A stream of research focused on models based on moments of distributions such as mean, variance, and skewness. Skewness preferences 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 Brunner et al. (2011).

ity of achieving extreme positive outcomes which might be aspiration levels. To the best of our knowledge no study has addressed yet the interaction of skewness with aspiration levels. As a consequence, it is desirable to disentangle choices explained by aspiration levels or preferences for skewness.[4]

Our experimental study has three main goals. The first is to replicate the preference *reversals*, as documented in the seminal work on aspiration levels of Payne et al. (1980). In the context of Payne's reversals we also aim to clarify the role of risk attitude and preference for skewness and hence adding to the understanding of such reversals. Our second goal concerns the interplay between aspiration levels and skewness preferences. To see whether choices are driven by aspiration levels, we use a large set of prospects with several features such that in some conditions aspiration levels can be used to predict choices while in other conditions aspiration levels are not predictive. In the former case, the resulting choice patterns characterize a heuristic for reducing the complexity of risky decisions. Where conditions are such that aspiration levels cannot be used to make predictions, we test for whether preferences for skewness might explain choices. The design allows, for the first time, to explore the interplay between preferences for skewness and aspiration levels by comparing the overall probability of winning or losing and the skewness between prospects. In addition, we investigated the role of the zero outcome. In fact, in light of the evidence of Diecidue et al. (2015) against an aspiration level at zero, we suspect that zero can become an aspiration level depending on the context, i.e. depending on whether zero is seen as a winning opportunity or not. Finally, the third goal of our study is to provide a rigorous model fitting of the most popular compensatory models of risky choices (EU and CPT) and -for the

[4]Skewness has been investigated in the domain of neuroscience: Wu et al. (2011) used functional magnetic resonance imaging to investigate the neural correlates of skewness preferences in financial decision making. In another fMRI study, Symmonds et al. (2011) investigated the neuronal sensitivity to skewness in risky choices.

first time- for their versions augmented with aspiration levels and thereby identify which one best fits the data from our experiment.

Our data replicate the preference reversals of Payne et al. (1980) and add new angles on the role of skewness in such a context. We show that aspiration levels and probability of winning predict choices and that in the conditions where aspiration levels alone are unable to make a clear predictions, preference for skewness is called for. Finally, while aspiration levels improve significantly the fit of EU, the best fit model still remains CPT. Our results, while corroborating the idea that the descriptive success of CPT maybe in part driven by preference for skewness (Ebert 2015, Spiliopoulos and Hertwig 2015), stress the role of skewness in decision under risk and its relation to aspiration level. We conclude that new models based on aspiration levels and moments such as skewness may be a promising avenue of research (Spiliopoulos and Hertwig 2015).

In the next section 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 was paid a fixed participation fee; subjects were also paid an extra amount as a function of their performance on one (randomly selected) trial. The experiment was computer based and the experimental conditions were shown in a random fashion. Instructions were given at the beginning of each experimental session. The study was approved by the local ethical committee.

2.2 Experimental Design

The experiment consisted of 168 choices, without feedback, between pairs of three-outcome prospects having the same expected value and different probabilities of winning and losing. We believe that such multi-outcome mixed prospects are suitable to test models of choice that rely on aspiration levels and skewness.[5] Spiliopoulos and Hertwig (2015) consider three-outcome prospects significantly more informative than two-outcome prospects and Diecidue et al. (2015) did not find any difference in terms of aspiration levels when considering prospects with more than three outcomes. For these reasons, given that we are interested in exploring both aspiration levels and skewness, we restricted our attention to cases involving three possible outcomes. The outcomes were monetary and an example of stimuli is shown in the appendix on Fig 3. The 168 trials were clustered into 16 conditions (from L1 to L16).[6]

Conditions L1, L2, and L3 were designed to test for the presence of classic preference reversals (Payne et al. 1980) and to measure two novel aspects with respect to their original design—namely, attitudes toward risk and skewness. 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; in L3, all the outcomes of L1 were *increased* by €30. Our prediction was that a change in risk attitude should be observed when moving from L2 to L3 because subjects were dealing with mostly negative outcomes in L2 but with mostly positive outcomes in L3.

Conditions from L4 to L15 were designed to test for the presence of aspiration levels, skewness preferences, and the contextual role of the outcome zero. In conditions L4, L5, L6, L7, L8, L9 there are two possible cases: first in *both* prospects

[5]Ebert (2015) showed that skewness preferences can be identified with binary prospects.

[6]The Appendix gives a summary of all the conditions.

it is possible or not possible to achieve aspiration levels (i.e. L7, L8), in the second case *only one* prospect provides the possibility to achieve aspiration levels (i.e. L6, L9). In conditions L10, L11, L12, L13, L14, L15 there are also two possible cases: first in *both* prospects there is the possibility or the *certainty* to achieve aspiration levels (i.e. L15, L12), in the second case *only one* prospect provides the *certainty* to achieve aspiration levels (i.e. L14, L13). Conditions L4, L5, L10, L11 have one prospect with a payoff equal to zero. In these conditions it might be possible to predict choices depending on the contextual role of zero, i.e., whether zero is positively or negatively evaluated.

This design enabled us to test in which situations choices are affected by aspiration levels. In conditions where *only one* prospect provides the possibility or certainty to achieve aspiration levels, we expected that subjects would choose that prospect allowing them to reach their respective aspiration levels. In the other conditions under which aspiration levels are not predictive of subject choices we expected that subjects' preferences for the prospect with the highest skewness would explain their choices.

Finally, the choices in condition L16 are the only one that involve prospects with *different* expected values. This condition was added to allow comparisons with the other conditions, each of which features *no* difference in expected value. In this last conditions, subjects can easily detect the prospect with the highest expected values focusing on both 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.

	L1 (Basic)	L3 (Basic + 30)	L2 (Basic − 30)
% Choices	0.51	0.61	0.37

Table 1: Proportion of Choices for Prospect B

Table 1 shows that, in L1, the chances of prospect A or prospect B being chosen are practically the same. In condition L3, we added €30 to the outcomes of each prospect; this *increased* the overall probability of winning. Our experimental data show that the proportion of choices for the prospect B (whose three possible outcomes now all have positive values), increased from 0.51 to 0.61. At the other extreme, in condition L2 we subtracted €30 from the prospect outcomes and thus *increased* the overall probability of losing. Here our data show that the proportion of subjects choosing prospect B (whose three outcomes are now all negative) declines from 0.51 to 0.37. We ran the Wilcoxon signed-rank test among 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 also $p < 0.001$ for L3 versus L2.

After analyzing the proportion of choices in L1–L3, we ran two random-effects logistic models conjointly on L1, L2, and L3; the results are given in Table 2. In Model 1 we tested for the effect on choices of the *difference*—between the two prospects—in the probability of winning (dPrWin) and of losing (dPrLoss). The results indicate that choices are driven by the overall probability of winning. In Model 2, we assessed the effect of the difference in standard deviation (dSD) and in skewness (dSkw) on choices between the two prospects. The skewness value of each prospect is computed as the standardized third statistical moment. The difference in standard deviation reflects attitudes toward risk: a statistically not significant dSD implies risk neutrality; a positive (resp., negative) effect on choices implies risk seeking (resp., risk aversion). The data show a nonsignificant

Table 2: Two Models for Choices in L1, L2, L3

	Model 1	Model 2
	choice	choice
dPrWin	2.061***	
	(5.74)	
dPrLoss	0.511	
	(1.46)	
dSD		0.00236
		(1.01)
dSkw		0.179***
		(3.35)
_cons	-0.168*	-0.0556
	(-2.04)	(-0.57)
N	2018	2018

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

dSD. The difference in skewness reflects attitudes toward skewness: a statistically not significant dSkw implies a neutral attitude toward skewness. A (significant) positive sign of the difference in skewness implies preference for positive skewness and dislike for negative skewness; the opposite holds in the case of a negative (significant) difference. The results show that the overall choices in L1, L2, and L3 are driven by the extent of positive skewness.

Table 3: Risk Attitude and Skewness Preferences in: L1, L2, L3

	(L1)	(L2)	(L3)
	choice	choice	choice
dSD	-0.000673	0.0257***	-0.0170***
	(-0.16)	(5.94)	(-3.97)
dSkw	0.194*	0.136	0.256**
	(2.05)	(1.38)	(2.63)
_cons	0.107	-0.133	-0.145
	(0.72)	(-0.84)	(-0.92)
N	670	673	675

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Given the results of Table 2, we ran three additional logistic regressions to measure, independently for each condition, attitudes toward risk and skewness (see Table 3 for the results). Given that the outcomes are almost all negative in L2 yet are almost all positive in L3 (see Table 7 in the Appendix), we expected to find that risk attitudes are reversed in L3 with respect to L2. Indeed, Table 3 confirms that subjects are risk seeking under L2 (choosing among prospects with mostly negative outcomes) but are risk averse under L3 (prospects with mostly positive outcomes). The difference in skewness is positive and significant in L1 and L3.

3.2 Aspiration Levels and Preferences for Skewness

We used conditions from L4 to L15 for three purposes: (i) to test for the presence of aspiration levels, (ii) to understand how subjects evaluate the zero outcome as a function of the context, and (iii) to check whether subjects choices could be explained by skewness preferences.

Our *first* prediction was that in conditions where *only one* prospect provides the possibility to achieve aspiration levels, subjects would choose that prospect allowing them to reach their respective aspiration levels (e.g., prospect B in L9). Thus an even stronger preference should be observed for a prospect that guarantees an outcome above those aspiration levels, i.e. aspiration certainty, (A in L13). Our *second* prediction was that—in L4, L5, L10, and L11—the outcome 0's perceived "sign" would depend on the sign of the other two outcomes in the same prospect. For example, a preference for prospect A in L4 (resp., B in L10) would suggest that 0 is perceived as a nonnegative (resp., nonpositive) value. Finally, our *third* prediction was that, in conditions under which choices are not explained by aspiration level (L7, L8, L12, L15), they could be explained by preferences for positive skewness.

Table 4 reports for each condition the proportion of choices for the prospect A and B. In the conditions where choices might be predicted by aspiration levels alone or by the subjective perception of zero (positive or negative), this prediction is reported in the columns Ch.Prediction.

Cond	% Choices A	% Choices B	Ch.Prediction	Cond	% Choices A	% Choices B	Ch.Prediction
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 4: Proportion of Choices and Choices Predictions.[1]

[1] **Note:** In the columns Ch.Prediction we report whether the choices are explained by aspiration levels (AL), by aspiration certainty (ALc), and whether the zero outcome is perceived as positive or negative (Pos and Neg, respectively). Significant differences in proportions of choices are reported in bold with $^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$.

- Under L4, prospect A has an outcome equal to 0 and all the other outcomes are negative (in both prospects A and B). Hence subjects' choices might vary depending on whether the 0 is perceived as being positive or as negative. In L4 we observed a preference for prospect A; in L5, we observed a preference for prospect B (whose positive outcome is 8). This finding suggests that subjects evaluate the value of 0 in L4 as being positive—that is, when compared with the other (negative) outcomes that could result from choosing this prospect. In L5 choices seem to prefer prospect B which has the only one positive value 8.

- Under condition L6 we were expecting a preference for prospect A, which is the only prospect providing the possibility to achieve an aspiration level (i.e., 2). Even if prospect A has been chosen more than prospect B, such difference is not significant. Under L7, where both prospects provide the possibility to achieve aspiration levels, choices could be predicted by preferences for skewness.

- Under condition L8, all the values (both in prospect A and in prospect B) are negative. This is a condition under which aspiration levels cannot be reached, so choices could be explained instead by attitudes toward skewness. In contrast, in L9 prospect B has at least one positive outcome. As expected, we observed a preference for B where there is a nonzero probability of that prospect's outcome matching (or exceeding) the subject's aspiration level.

- Under L10, prospect A has an outcome equal to 0 and prospect B has only positive outcome values. Here, as in L4, subjects' choices might vary depending on how the outcome 0 is perceived; in this condition we observed a clear preference for prospect B, all of whose values exceed 0. Under L11, again prospect A has an outcome equal to 0 and two other outcomes of positive value while prospect B has a negative value (-50). Here the subjects favored prospect A.

- Under L12, both prospects provide the certainty to achieve aspiration levels (all values of both prospects are positive). Just as in L8, L7 and L15, under this lottery condition the observed choices are not explained by aspiration levels alone. Under condition L13, however, only prospect A gives the certainty to achieve aspiration levels. As aspiration levels would predict, a clear preference is observed for A because that choice is associated with aspiration certainty.

- Under L14, we observed (as expected) a clear preference for prospect B, the choice that guarantees achieving an outcome whose value exceeds zero. This condition corresponds to *aspiration certainty* because, if B is chosen, then the probability of achieving an aspiration level is 1. Under L15, each prospect provides the possibility to achieve an aspiration level. In this condition, aspiration levels alone are insufficient to account for the experimental subjects' observed choices, thus we will check for skewness preferences.

In sum: under this section's tested conditions (from L4 to L15), we found that subjects' choices are in most cases predicted by aspiration levels. In order to disentangle the possible cases in which aspiration levels and skewness preferences could overlap (i.e. when the DMs choose the prospect providing aspiration levels and the highest skewness), we ran a regression restricted to the cases where the prospect having aspiration levels is the one with the lowest skewness. If choices were explained by the simplified approach based on aspiration levels only, rather than preferences for skewness, we should observe that the difference in skewness "dSkw" is significant and negative given that the chosen lottery (the one with aspiration levels) has the lowest skewness. Indeed, we found that in these specific cases the "dSkw" is significant with negative sign, $p.val < 0.001$.

In all other cases where aspiration levels are *not* predictive, choices might rely on a compensatory approach (i.e. skewness preferences). Thus, we ran a logit regression for which the regressors were the difference in the probability of winning (dPrWin) and losing (dPrLoss), the difference in standard deviation (dSD), and the difference in skewness (dSkw). The results are reported in Table 5.

Model 1 of Table 5 refers to conditions (L7, L8, L12, L15) and shows a significant probability of winning. In addition it shows that in conditions where aspiration levels cannot predict choices, the difference in skewness is significant and positive thus confirming our prediction that, in prospects where aspiration levels cannot be reached, choices are driven by preferences for positive skewness. This result is in line with those reported in previous studies (e.g., Astebro et al. 2014, Ebert 2015, Spiliopoulos and Hertwig 2015), where skewness has been found to play a pivotal role in risky choices.

Model 2 of Table 5 refers to condition L16 which involves prospects with different expected value. The logistic regression shows that the only significant regressors are the difference in standard deviation (dSD) and the difference in expected

Table 5: 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)
Evd		0.110***
		(3.97)
_cons	-0.143	0.0760
	(-1.49)	(0.71)
N	1834	479

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

value (dEV). These results confirm that in the conditions when there is no possibility to undertake a simplified strategy, subjects will go through a compensatory approach that might rely on (the difference in) expected value and the (difference in) positive skewness. This is in line with Erev et al. (2015) which reported the predictive power of models relying on expected value plus simplifying heuristics.

3.3 Response Times

Figure 1 graphs subjects' response times (in centiseconds) under each lottery condition, and it shows a high degree of heterogeneity. However we detect that choices are made more rapidly than the average under L3, L10, and L13; they are made more slowly than average under L1, L8, and L16.

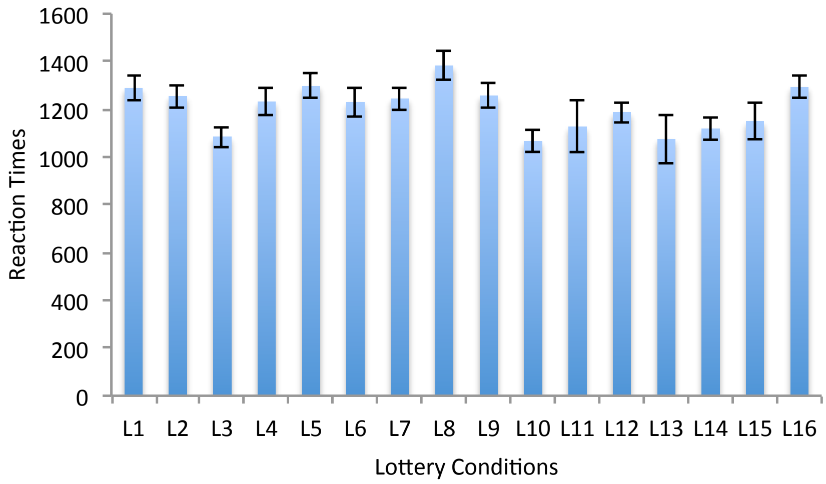

Figure 1: Response Times (cs) under the 16 Tested Conditions

Figure 2 graphs subjects' response times under these two main groups. The difference between these two groups is significant ($\chi^2 = 31.92\, p.val < 0.001^{***}$). In the former trio we find three conditions where choices can be explained by a

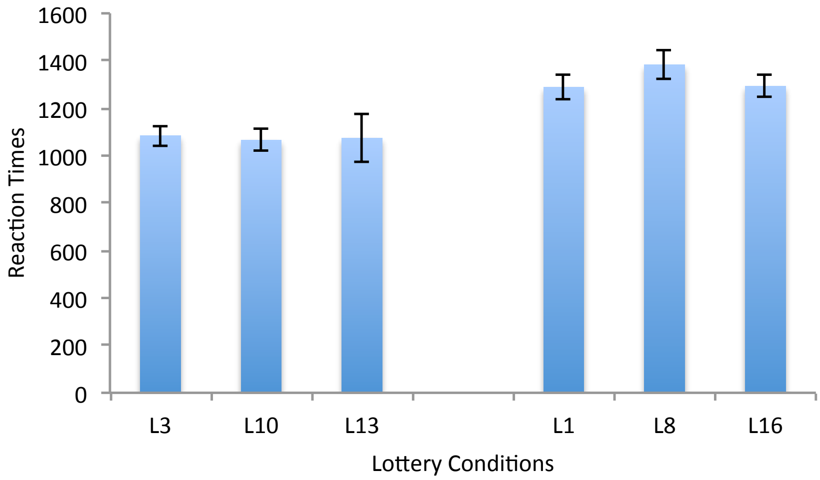

Figure 2: Response Times (cs) under two Groups of Conditions

simplified strategy; the latter trio includes conditions where choices might rely on a different decisional approach. Indeed, we suppose that choices in the "fast" group of lotteries are driven by a simplifying strategy that is not mentally taxing. Choices in the "slow" group might instead be driven by a compensatory strategy that imposes a greater cognitive load.

4 Model Fitting

In addition to the analyses just described, we also performed a maximum likelihood estimation (MLE) toward the end of fitting our experimental subjects' actual choices to the most popular (compensatory) models of decisions under risk. We focused on expected utility, cumulative prospective theory, and their hybrid versions such as EU with aspiration levels (EU&AL) and CPT with aspiration levels (CPT&AL). To the best of our knowledge there is not in the extant literature an analysis based on MLE of models including aspiration levels. In this approach, we first adopted one of the listed utility models and a range of values for the various relevant parameters. Then, given the observed choices, we computed the likelihood (transformed by the natural logarithm) and adjusted the estimated parameters so as to *maximize* the log-likelihood.

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. Without loss of generality, we assume that outcomes are rank ordered from best to worst; that is, prospect $X = (p_1, x_1; \ldots; p_n, x_n)$ satisfies $x_1 \geq \cdots \geq x_n$. So if we take an EU model with a power function $U(x_j) = x_j^{\alpha}$, then 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 $F(V) = (1 + e^{-\varepsilon(V_1 - V_2)})^{-1}$. Thus the conditional log-likelihood can be written as

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

where $y_i = 1$ or 0 according as whether, in trial i, the DM chose prospect A or prospect B.

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*, $P(x^-)$ the *overall probability of losing* and the parameters μ^+ and λ^- measure the effect of aspiration success and of aspiration failure, respectively. The valuation of a prospect X with outcomes x_j $(j = 1, \ldots, n)$ and probability p_j $(j = 1, \ldots, n)$ is equal to:

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

Hence the conditional log-likelihood under this theoretical model is

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

where again $y_i = 1$ or 0 according as whether, in trial i, the DM chose prospect A or prospect B. Under this model, we must estimate not only the utility function's parameter α but also μ^+ and λ^-. Thus there are three parameters to estimate.

In addition to the two previous models, we checked to see how well cumulative prospect theory (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 assumed that $w(p)$ is the Prelec (1998) two-parameter weighting function, which is defined as $w(p) = \exp\{-\delta(-\ln p)^\gamma\}$.

The conditional log-likelihood under cumulative prospect theory is

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

as before, $y_i = 1$ (resp., $y_i = 0$) means that, in trial i, the DM chose prospect A or prospect B. In this model there are seven parameters to estimate.

A fourth model integrates cumulative prospect theory with aspiration levels and also incorporates positive and negative utility jumps (see Diecidue & van de Ven 2008). Note that this model used *decision weights* in place of the *probabilities* used in eq. (1). Thus the conditional log-likelihood for this model specification is

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

once again, $y_i = 1$ (resp., $y_i = 0$) means that, in trial i, the DM chose the prospect A or prospect B.

Table 6 reports the estimated parameter values in the four models tested.[7] We also computed—and report values of—the Akaike information criterion (AIC) as an adjusted measure of model selection, where AIC $= -2\ln L + 2k$ for k the number of model parameters. The table's last two rows report the (negative) log-likelihood and the AIC in order to identify the best-fitting model. Our analysis show that aspiration levels improve the fit of EU and that both CPT and CPT&AL perform better than either EU or EU&AL, respectively. According to the AIC, the model that best fits the data is CPT with an AIC value of 219.314. The data in Diecidue et al. (2015) were also consistent with standard parameterizations of CPT. In overall, our results in Section 4 support the view that one important aspect of decision under risk is the preference for skewness and the MLE analysis shows that CPT is the best equipped model to capture it.

Finally, the two models incorporating AL allow us to measure (in addition to the the other parameters) μ^+ and λ^- for the first time. These parameters were introduced in the aspiration level model of Diecidue and van de Ven (2008) implying that the utility function is discontinuous and jumps at zero. The estimated values

[7] Previous 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).

Parameter	EU	EU&AL	CPT	CPT&AL
α	0.913	0.871	0.267	0.262
β	—	—	0.349	0.376
λ	—	—	1.118	1.071
δ^+	—	—	0.800	0.836
γ^+	—	—	0.677	0.698
δ^-	—	—	1.325	1.457
γ^-	—	—	0.417	0.572
μ^+	—	1.046	—	0.296
λ^-	—	0.521	—	0.738
Log-likelihood	-119.461	-114.783	-102.657	-101.369
AIC	240.922	235.568	219.314	220.737

Table 6: MLE Parameters

of μ^+ and λ^- suggest that, at the aggregate level, there is *not* an appreciable jump at zero. This finding, while providing the first quantitative measurement of the parameters, confirms the results of Diecidue et al. (2015) and their explanation that this absence of a jump may be due to heterogeneity in aspiration levels. In addition, our data show that this absence of a jump at zero may be also explained by the contextual role of the zero outcome.

5 Discussion

We used a variety of conditions, involving choices with prospects of same expected value, to identify different behavioral patterns and aspects of choices under risk. These conditions can be divided in three main groups. The *first* group consists of conditions L1, L2, and L3. The paired prospects in these conditions were used to test for the classic preference reversals, as first reported by Payne et al. (1980), and thereby to measure—via logistic regression their effect on the overall probability of winning and losing. In addition we also studied risk attitudes and the effects of skewness on these classic choices between prospects so adding to our understanding of Payne's results. To that goal, we introduced in our analysis, as regressors, the difference between prospects in terms of standard deviation and skewness so we could reliably assess how choices are affected by attitudes toward risk and preference for skewness.

We found evidence (and hence replicated) for preference reversals. This behavioral pattern is an heuristic of decision under risk that links choices 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). This finding is corroborated by the significant effect of the differences in the probability of winning (Model 1 in Table 2). We remark that decision makers are more strongly affected by the likelihood of winning than that of losing; indeed, we found the latter effect to be not significant showing that the probability of winning looms larger than the probability of losing. This evidence is in line with Payne (2005) and Venkatraman et al. (2014) results and also replicated by Erev et al. (2015); however, in financial decisions, Zeisberger (2014) found a significant effect of the probability of losing.

In terms of risk attitude, transforming L1 into L3 (resp. L2) by increasing (resp. decreasing) all payoffs by €30 affects, as we predicted, the choice responses of our experimental subjects. As reported in Table 3, under L2 (reduced payoff) the difference in standard deviation has a significantly positive effect on subjects' choices—that is, on the likelihood of prospect B being selected—and is indicative of a risk-seeking attitude; conversely, under L3 (increased payoff) this difference (dSD) has a significantly negative effect on that likelihood and signifies a risk-averse attitude. The results on risk attitude are therefore in line with the predictions of CPT.

More importantly, when replicating the original set of choices of Payne et al. (1980), we found a -novel- significant effect of the difference in skewness: We observed (Model 2 of Table 2) a preference for positive skewness differences between prospects with equal expected value. We zoomed into this evidence: Table 3 reports that the difference in skewness is positive and significant in L1 and L3, it is not significant but in the predicted direction for L2.[8] This result underlies a preference for positive skewness and aversion for negative skewness. The latter result, together with the significance of the probability of winning, suggests that subjects are motivated to achieve aspirations by choosing prospects that include even extreme positive values as in Astebro et al. (2015) reflecting "overweighting" of relatively improbable outcomes.

The *second* group includes conditions from L4 to L15. The aim of these conditions was to inform us concerning the presence of aspiration levels, subjects' context-dependent evaluations of the "zero" outcome, and the effect (on choices) of skewness preferences. The conditions allowed us to understand when aspiration levels are predictive of choices and when they fail to do so and, as a consequence, preference for skewness matters. We detect the different conditions where simplifying strategies, based on aspiration level, or compensatory strategies, based on preferences for skewness, are in place. We found that decision makers opt for the prospect that offers a nonzero probability of achieving their aspiration levels (i.e., the likelihood of a positive outcome). There is also a strong preference for prospects whose outcomes are such that the achievement of aspiration levels is guaranteed, or (in other words) that yield what we call aspiration certainty. This behavioral pattern, which accords with choices indicated by the "probability of

[8]When removing the variable dSD, dSKw becomes significant for L2 too.

winning" heuristic, is illustrated in Table 4. In conditions that include a zero outcome, this value is perceived as positive (nonnegative) when the prospect's other outcomes are all negative values yet is perceived as negative (nonpositive) when those outcomes are all positive. Indeed, our data confirm that subjects clearly prefer the prospect that includes 0 in L4 even as they clearly do not prefer the prospect that includes 0 in L10.

In the other conditions, (L7, L8, L12, L15) aspiration levels alone do not allow a clear prediction of choices. That is: 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 decisive in the subject's choice. In these cases we were led to test for the effect of preferences for skewness. We found that the difference in skewness (dSkw) between chosen versus unchosen prospects is statistically significant in all these conditions and thus suggests that, ceteris paribus, subjects prefer the prospect with the greater positive skewness and with the smaller negative skewness. We believe that this preference for extreme positive values, together with a significant probability of winning, is subsumed by the more general behavioral pattern that reflects aspiration levels. Nonetheless, for lotteries (e.g., L8) in which prospect outcome values fall short of aspiration levels and for lotteries (e.g., L12) in which prospect choices are not fully explained by aspiration levels, observed behavior can be explained only if both factors—aspiration levels and probabilities—are considered. The skewness of each prospect depends on both the probabilities and values of payoffs, which is why we believe that the *difference* in skewness between prospects is a good candidate for predicting choices. By and large, the experimental results confirm our predictions. We were able to measure the preference for skewness (Astebro et al. 2015, Ebert 2015) and to detect its relevant effect on choice under risk. Although aspiration levels and probability of winning are relevant, they are not the only aspect of choice that matters (Diecidue and van de Ven 2008).

Finally, the *third* "group" consists only of L16. This is the sole condition whose prospects entail *different* expected value, a feature that should prove useful for testing whether—for such prospects—the subject's decision process reflects a simplifying or rather a compensatory strategy. Recall from Model 2 of Table 5 that, among the regressors we employed, 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 could be explained simply by the 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 conditions are such that the choice of prospect (i.e., A versus B) should be easy and is well predicted by aspiration levels; the "slow" group includes conditions in which choices for which aspiration levels alone do not account—suggesting the application of a different kind of decision process. We conjecture that prospect choices in the fast group of conditions are driven by a *simplifying* strategy (i.e., aspiration levels), since heuristics of that type are typically fast and cognitively undemanding; at the same time, we posit that choices in the slow group are driven by a *compensatory* strategy that entails a greater cognitive load. These considerations suggest that multiple decision processes (for example Erev et al. 2015) could be in play depending on the (risky) prospect's attributes.

According to the maximum likelihood estimation performed in Section 5, cumulative prospect theory best fits the observed choices. Although the aspiration model with jumps at zero (Diecidue & van de Ven 2008) improves the fit when compared with a strict expected utility approach, a like improvement is *not* observed when we compare cumulative prospect theory with a model that also incorporates aspiration levels (CPT&AL). Our methodology allows us to measure for the first time the parameters of the models augmented by aspiration levels. The values of μ^- and λ^- (which are presumed to measure the magnitude of the positive and negative jumps around zero) are relatively small. This evidence fails to support the jumps at zero and it is in line with Diecidue et al. (2015). This result is likely the consequence of Diecidue and van de Ven (2008)'s model failing to account for the heterogeneity in aspiration levels, as later suggested in Diecidue et al. (2015). The obtained result in favor to cumulative prospect theory is in line with our previous analysis on preferences for positive skewness. The link between CPT and preferences for skewness relies on the optimism and likelihood insensitivity which are two aspects captured by CPT through its probability weighting functions.

In summary: our research investigated the conditions under which simplifying strategies, such as that aspiration levels, play a role in predicting decision under risk. It is remarkable that Erev et al. (2015) demonstrated that a general class of models apt to describe decision under risk is made out of expected value (compensatory) plus heuristics as simplifying tie-breaking rules, hence stressing the importance of both decision processes. In the vast majority of our experimental questions (from L1 to L15) the expected value was the same between the two prospects under consideration, as a consequence we enhanced the role of heuristics. In addition, our research showed that DMs have preferences for skewness and that this preference is naturally related to aspiration levels and overall probability of winning. In terms of models capturing this evidence, CPT still dominates models that include aspiration levels. CPT manages to model preference for skewness in an implicit but very effective way through the overweighing of small probabilities. We conclude that CPT remains a very powerful model to describe decision under risk. Our research clarifies that one reason of its descriptive power relies on the implicit role that skewness play in the probability weighting function of CPT.

6 Conclusion

In this empirical study we confirmed the existence (as first posited by Payne et al. 1980) of preference reversals, which accord with findings on the "probability of winning" heuristic. We also found that our experimental subjects prefer the prospect offering a nonzero probability of achieving aspiration levels; a strong behavioral preference is quite naturally observed for prospects that *ensure* the achievement of those levels, ie, aspiration certainty. In conditions where aspiration levels alone are insufficient to predict choices, preferences for positive skewness explain the subjects' choice behavior. The results of our maximum likelihood estimation indicate that cumulative prospect theory is the one that best fits our data. We observe that preference for skewness, as captured by its probability weighting function may contribute to the descriptive appeal of this theory. In addition, CPT is the model that best fits the observed choices. This may be due by the context dependent role of zero and by the existence of heterogenous aspiration levels.

Overall, our results strongly suggest that the optimal strategy for dealing with risky prospects depends on (among others) such factors as structure, information, and complexity. In line with 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., probability of winning or 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 evidences a multiple strategy approach to decision making.

Appendix

	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 7: The all 16 experimental conditions. All other pairs of prospects played by subjects have the same qualitative structure but different payoffs.

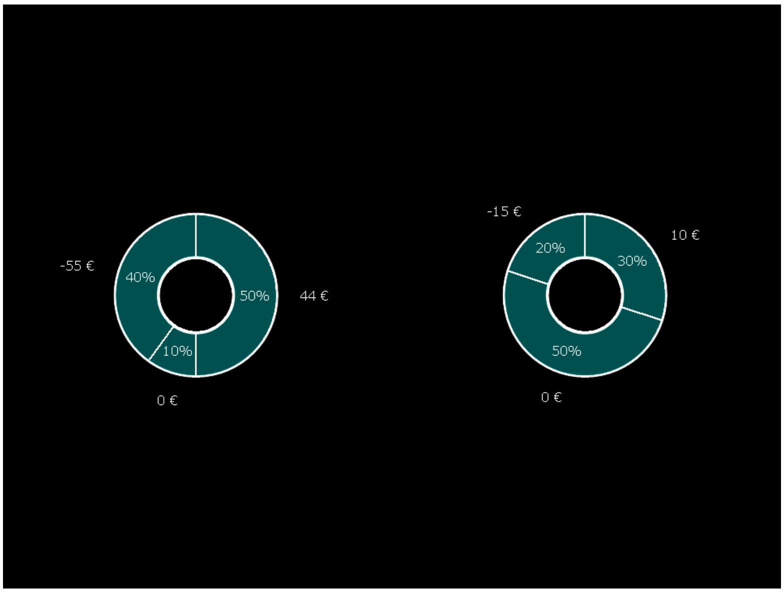

Figure 3: Choice Between Two Prospects

Figure 3: An example of stimuli presentation.

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