Modeling Gain-Loss Asymmetries in Risky Choice: The Critical Role of Probability Weighting

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Abstract

A robust empirical regularity in decision making is that the negative consequences of an option (i.e., losses) often have a stronger impact on people's behavior than the positive consequences (i.e., gains). One common explanation for such a *gain-loss asymmetry* is loss aversion. To model loss aversion in risky decisions, prospect theory (Kahneman & Tversky, 1979) assumes a kinked value function (which translates objective consequences into subjective utilities), with a steeper curvature for losses than for gains. We highlight, however, that the prospect theory framework offers many alternative ways to model gain-loss asymmetries (e.g., via the weighting function, which translates objective probabilities into subjective decision weights; or via the choice rule). Our goal is to systematically test these alternative models against each other. In a reanalysis of data by Glöckner and Pachur (2012), we show that people's risky decisions are best accounted for by a version of prospect theory that has a more elevated weighting function for losses than for gains but the same value function for both domains. These results contradict the common assumption that a kinked value function is necessary to model risky choices and point to the neglected role of people's differential probability weighting in the gain and loss domains.

Keywords: cognitive modeling; loss aversion; risky choice; prospect theory; probability weighting

Introduction

For many of our decisions we are unable to tell with certainty what consequence the decision will have—for instance, when deciding between different medications that potentially lead to some side effects. Ideally, we have knowledge of the nature of the possible consequences as well as some inkling of the chances that the consequences will occur, but our decisions must necessarily remain in the "twilight of probability" (Locke, 1690/2004). Elaborating how such risky decisions are made (and how they should be made) has engaged decision scientists at least since Bernoulli's (1738/1954) seminal work on subjective utility.

One of the most influential and successful modeling frameworks of risky decision making is prospect theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). A prominent feature of prospect theory is the assumption that the subjective disutility of a negative outcome is higher than the subjective utility of a positive outcome of the same size. In other words, prospect theory assumes an asymmetry between gains and losses in its value function, which translates objective outcomes into subjective magnitudes. This assumption of *loss aversion* can explain, for instance, that people dislike gambles in which one has a 50% chance to win a particular amount of money and a 50% can to lose the same amount. Similarly, loss aversion is invoked to account for the endowment effect—the phenomenon that people evaluate an object higher in a buyer perspective than in a seller perspective (e.g., Pachur & Scheibehenne, 2012; for a general overview of gain-loss asymmetries, see Peeters & Czapinski, 1990).

However, the way prospect theory—more specifically, its mathematical formulation in *cumulative prospect theory* (CPT; Tversky & Kahneman, 1992)—is usually implemented allows for asymmetries in the evaluation of positive and negative prospects to be represented also in other ways than via the value function. For instance, the parameters of CPT's weighting function, which translates objective probabilities into subjective decision weights, are typically estimated separately for the gain and the loss domain (e.g., Gonzalez & Wu, 1999). Furthermore, it has been argued that choice sensitivity (i.e., how accurately choices between two alternatives reflect their subjective valuations) differs between options involving losses and those involving gains only (Yechiam & Hochman, 2013a).

Crucially, these possible representations of gain-loss asymmetries within CPT have never been directly pitted against each other in a model-comparison analysis (Linhart & Zucchini, 1986), where the descriptive power of a model is evaluated in light of its complexity (but see Harless & Camerer, 1994; Stott, 2006). Conducting such a model comparison is our goal in this paper. To that end, we use CPT to model data collected by Glöckner and Pachur (2012), where 64 participants were asked to make choices between 138 two-outcome monetary gamble problems.[1] Fitting different implementations of CPT to this data also allows us to test specific predictions of how a gain-loss asymmetry should be reflected in specific parameter patterns, such as *choice sensitivity* (Yechiam & Hochman, 2013a) or *probability sensitivity* (Wu & Markle, 2008). Next we provide a detailed description of CPT's parameter

[1] In Glöckner and Pachur (2012) each participant made choices between 138 gamble problems at two separate sessions (separated by one week). Here we analyze the data from the first session.

framework, which we then use to formalize different ways to represent gain-loss asymmetries in risky decision making.

Cumulative Prospect Theory

According to CPT, the possible consequences of a risky option are perceived as gains or losses relative to a reference point. The overall subjective value V of an option with outcomes $x_m > \ldots \geq x_1 > 0 > y_1 > \ldots > y_n$ and corresponding probabilities $p_m \ldots p_1$ and $q_1 \ldots q_n$ is given by:

$$V(A) = \sum_{i=1}^{m} v(x_i)\pi_i^+ + \sum_{j=1}^{n} v(y_j)\pi_j^- , \tag{1}$$

where v is a *value function* satisfying $v(0) = 0$; π^+ and π^- are *decision weights* for gains and losses, respectively, which result from a rank-dependent transformation of the outcomes' probabilities. The decision weights are defined as:

$$\begin{aligned}
&\pi_m^+ = w^+(p_m) \\
&\pi_n^- = w^-(q_n) \\
&\pi_i^+ = w^+(p_i + \ldots + p_m) - w^-(p_{i+1} + \ldots + p_m) \quad \text{for } 1 \leq i < \text{m} \\
&\pi_j^- = w^-(q_j + \ldots + q_n) - w^+(q_{j+1} + \ldots + q_n) \quad \text{for } 1 \leq j < \text{n}
\end{aligned} , \tag{2}$$

with w^+ and w^- being the probability *weighting function* for gains and losses, respectively (see below). The weight for each positive outcome represents the marginal contribution of the outcome's probability to the total probability of obtaining a better outcome; the weight for each negative outcome represents the marginal contribution of the outcome's probability of obtaining a worse outcome.

Several functional forms of the value and weighting functions have been proposed (see Stott, 2006, for an overview). In our analyses, we use the power value function suggested by Tversky and Kahneman (1992), which is defined as

$$\begin{aligned}
v(x) &= x^{\alpha} \\
v(y) &= -\lambda(-y)^{\beta}
\end{aligned} . \tag{3}$$

For α and β usually values smaller than 1 are found, yielding a concave value function for gains and a convex value function for losses. The parameter λ reflects the relative sensitivity to losses versus gains and is often found to be larger than 1, indicating loss aversion.

The weighting function has an inverse S-shaped curvature, indicating overweighting of unlikely events (i.e., those with a small probability) and underweighting of likely events (i.e., those with a moderate to high probability). Here we use a two-parameter weighting function originally proposed by Goldstein and Einhorn (1987), which separates the curvature of the function from its elevation (cf. Gonzalez & Wu, 1999):

$$\begin{aligned}
w^+(p) &= \frac{\delta^+ p^{\gamma^+}}{\delta^+ p^{\gamma^+} + (1-p)^{\gamma^+}} \quad \textit{for } x \\
w^-(q) &= \frac{\delta^- q^{\gamma^-}}{\delta^- q^{\gamma^-} + (1-q)^{\gamma^-}} \quad \textit{for } y
\end{aligned} . \tag{4}$$

γ^+ and γ^- (both < 1) govern the curvature of the weighting function in the gain and loss domains, respectively, and indicate the sensitivity to probabilities. The parameters δ^+ and δ^- (both > 0) govern the elevation of the weighting function for gains and losses, respectively, and can be interpreted as the attractiveness of gambling. In other words, δ^+ and δ^- also indicate a person's risk attitude, with higher (lower) values on δ^+ (δ^-) for higher risk aversion in gains (losses).

In addition to these core components of CPT, a choice rule is required when applying CPT to model binary choice. To derive the predicted probability of CPT that a gamble A is preferred over a gamble B we used an exponential version of Luce's choice rule:

$$p(A,B) = \frac{e^{\phi \cdot V(A)}}{e^{\phi \cdot V(A)} + e^{\phi \cdot V(B)}} , \tag{5}$$

where ϕ is a choice sensitivity parameter, indicating how sensitively the predicted choice probability reacts to differences in the valuation of gambles A and B. A higher ϕ indicates more deterministic behavior; with $\phi = 0$, choices are random.

Modeling Gain-Loss Asymmetries

As described in the previous section, the common approach to accommodate an asymmetric evaluation of positive and negative prospects is to assume a kinked utility function, for instance produced by $\lambda > 1$ (see also Usher & McClelland, 2004; Ahn, Busemeyer, Wagenmakers, & Stout, 2008). Note, however, that observed choices are modeled based on three intertwined components, a value function, a weighting function, and a choice rule, all of which could, in principle, represent an asymmetry between gains and losses. In the following, we describe how gain-loss asymmetries could be modeled within each these components.

Utility Accounts

The formalization of CPT's value function allows for two ways to represent a gain-loss asymmetry.

Differential weighting of losses and gains Tversky and Kahneman's (1992) original version of CPT accommodates a gain-loss asymmetry using the loss aversion parameter λ, with $\lambda > 1$ leading to a stronger impact of losses (relative to gains). As can be seen from Equation 3, the effect of λ is to multiplicatively magnify the utility of losses relative to the utility of gains, implying greater sensitivity to losses.

Differences in outcome sensitivity In many applications of CPT the exponent of the value function is estimated separately for gains and losses (cf. Fox & Poldrack, 2008). If the latter (i.e., β in Equation 3) is higher than the former (i.e., α in Equation 3), this could also lead to a kinked utility function, and thus a gain-loss asymmetry. Note that this pattern has been observed in studies that included pure gain and pure loss gambles (e.g., Abdellaoui, Vossmann, & Weber, 2005).

Probability Weighting Accounts

Equation 1 shows that according to CPT—as in other models in the expectation tradition—the evaluation of an option closely ties the outcomes to their probabilities, as both are combined multiplicatively. Therefore, an apparent gain-loss asymmetry in the choices might also be represented by assuming differences between gains and losses in probability weighting (Zank, 2010; see also Birnbaum, 2008). Existing studies that have estimated the weighting function separately for gains and losses show that doing so indeed partly absorbs a gain-loss asymmetry (and might decrease the estimated value of λ). In particular, the elevation is commonly found to be higher for losses than for gains (for an overview, see Fox & Poldrack, 2008). Nevertheless, it is currently unclear to what extent estimating different weighting functions for losses and gains interacts with the estimation of the λ parameter and whether the increased model flexibility gained by adding more parameters actually leads to better predictive performance.

Differences in probability sensitivity Wu and Markle (2008) highlighted that an asymmetry might not necessarily exist between gains and losses, but between problems with mixed gambles and problems with single-domain gambles (i.e., those that offer either only gains or only losses). They found support for a version of CPT that allows probability sensitivity to differ between mixed and single-domain problems, with a lower probability sensitivity for mixed gambles than for single-domain problems. Moreover, Wu and Markle showed that this version of CPT can account for violations of *gain-loss separability* (that the evaluation of outcomes and their respective probabilities is done separately for the gain and the loss domains, as shown in Equation 1), which is a fundamental assumption in Tversky and Kahneman's (1992) original description of CPT.

Choice Sensitivity Account

A radically different explanation for an asymmetry between the gain and the loss domain was proposed by Yechiam and Hochman (2013a). They argued that the somewhat inconsistent manifestation of loss aversion in risky choice studies might be due to the fact that processing information about potential losses increases the amount of attention allocated to the task at hand. According to Yechiam and Hochman, this should be reflected in a higher choice-sensitivity parameter in problems involving losses (i.e., pure-loss gambles and mixed gambles) as compared to problems involving gains only. In a task in which participants responded to sequentially learned risks and using a reinforcement model, Yechiam and Hochman (2013b) found support for this hypothesis; to our knowledge, it has not been tested in the context of description-based tasks and using CPT as modeling framework.

Which Model Provides The Best Account?

Several investigations have challenged the utility account of gain-loss asymmetries (e.g., Schmidt & Traub, 2002; Yechiam & Hochman, 2013a). However, one problem of these studies is that they focused on *specific* items and are thus silent with regard to the importance of the elements of utility accounts (e.g., the loss aversion parameter) for CPT's ability to describe risky choices more *generally*.

For a more general test, one needs to compare different CPT implementations (representing alternative accounts of gain-loss asymmetries) and to determine which fares best in trading off model fit and model complexity (Myung, 2000).

Such a modeling analysis also allows us to test hypotheses concerning specific parameter patterns predicted by some of these accounts. For instance, according to the choice-sensitivity account by Yechiam and Hochman (2013a) choice sensitivity should be higher in tasks involving losses than in tasks involving gains only. This hypothesis has not been tested directly in the context of description-based tasks.

A second hypothesized parameter pattern follows from the probability weighting account proposed by Wu and Markle (2008), according to which the probability sensitivity (i.e. the curvature of the weighting function) is lower for mixed gambles than for single-domain gambles. Wu and Markle found support for this pattern using Tversky and Kahneman's (1992) one-parameter weighting function; one limitation of this function is, however, that curvature and elevation are confounded. Whether the hypothesized parameter pattern also emerges when using a function that allows to disentangle curvature and elevation (e.g., using the two-parameter weighting function described in Equation 4) has not yet been tested.

Modeling Approach

To evaluate the different accounts of gain-loss asymmetries described above, we tested a total of 10 different implementations of CPT in their ability to describe people's risky choices. The implementations, which are summarized in Table 1, differ in terms of whether a gain-loss asymmetry is represented in the value function, the weighting function, or the choice rule.

Table 1: Versions of CPT tested.

	Outcome sensitivity	Probability sensitivity	Elevation	Loss aversion	Choice sensitivity	Free parameters
CPT_{nola}	α	γ	δ	$\lambda=1$	ϕ	4
CPT_{l}	α	γ	δ	λ	ϕ	5
CPT_{ab}	α β	γ	δ	$\lambda=1$	ϕ	5
CPT_{gd}	α	γ^{+} γ^{-}	δ^{+} δ^{-}	λ	ϕ	7
CPT_{d}	α	γ	δ^{+} δ^{-}	λ	ϕ	6
CPT_{dfixl}	α	γ	δ^{+} δ^{-}	$\lambda=1$	ϕ	5
CPT_{g}	α	γ^{+} γ^{-}	δ	λ	ϕ	6
CPT_{gfixl}	α	γ^{+} γ^{-}	δ	$\lambda=1$	ϕ	5
CPT_{phila}	α	γ	δ	$\lambda=1$	ϕ^{+} $\phi^{\pm/-}$	5
CPT_{gsm}	α	$\gamma^{+\vee-}$ $\gamma^{\pm}$	δ	λ	ϕ	5

CPT_{l} can be considered as the standard implementation of CPT. It assumes the same exponent in the value function

(Equation 3) for gains and losses (i.e., $\alpha = \beta$), but allows for a gain-loss asymmetry by having λ as a free parameter. CPT_l uses one common set of curvature (γ) and (δ) elevation parameters across the gain and loss domains. In a restricted version of CPT_l, CPT_{nola}, λ is set to 1 and thus assumes no gain-loss asymmetry. CPT_{nola} will serve as a benchmark model. CPT_{ab} also sets λ to 1 but allows the exponents of the value function to differ between gains (α) and losses (β).

CPT_{gd} is the model with the largest number of free parameters: it allows for differences between gains and losses both in curvature (γ^+ and γ^-) and elevation (δ^+ and δ^-) of the weighting function. The restricted versions CPT_d and CPT_{dfixl} allow a gain-loss asymmetry in the elevation only, thus assuming a single curvature parameter for gains and losses ($\gamma^+ = \gamma^-$); in CPT_{dfixl} λ is set to 1. CPT_g and CPT_{gfixl} allow a gain-loss asymmetry in the curvature of the weighting function only, thus assuming a single elevation parameter ($\delta^+ = \delta^-$); for CPT_{gfixl} λ is set to 1.

The two remaining models, CPT_{phila} and CPT_{gsm} implement the proposals by Yechiam and Hochman (2013a) and Wu and Markle (2008), respectively. CPT_{phila} assumes a gain-loss asymmetry neither in the value function (i.e., λ = 1) nor in the weighting function ($\gamma^+ = \gamma^-$ and $\delta^+ = \delta^-$); instead, it allows for separate choice sensitivity parameters in gambles involving losses ($\phi^{\pm/-}$) and gambles involving gains only (ϕ^+). CPT_{gsm} assumes no gain-loss asymmetry in the value function, but allows for different curvatures of the weighting function for single-domain gambles ($\gamma^{+\vee-}$) than for mixed gambles ($\gamma^{\pm}$).

The models were fitted to individual participants using the maximum-likelihood method. In order to avoid local minima, the optimization algorithm was supplemented with an initial grid search (considering up to 80,000 value combinations of the entire parameter space, with all parameters partitioned similarly).

To evaluate the models, we relied on the Bayesian Information Criterion (BIC), which penalizes a model as a function of its number of free parameters (Schwarz, 1978). The BIC of a given model is given by:

$$BIC = -2\log(f(d|\hat{\theta})) + \log(N)\,k, \qquad (6)$$

with d denoting the data, N the number of data points (i.e., the number of gamble problems), and k the number of free parameters in the model. BIC is an approximation of the Bayes Factor (Kass & Raftery, 1995), providing a theoretically-principled framework for model comparison that takes into account goodness of fit as well as model complexity (e.g., Myung, 2000). A lower BIC indicates a better model fit.

Data We applied the different CPT implementations to model individual data in Glöckner and Pachur (2012).[2] In this study, 63 participants (25 male, mean age 24.7 years) indicated their preferences between 138 two-outcome monetary gamble problems that contained 70 pure gain, 30 pure loss, and 38 mixed gambles, all drawn from sets of gamble problems used in previously published studies (see Glöckner & Pachur for details). The outcomes of the gambles ranged from -1000 € to 1200 €. At the completion of each session, one of the chosen gambles was picked randomly, played out and the participant received an additional payment proportional to the resulting outcome.

Results

Is there a Gain-Loss Asymmetry in the Value Function?

For the standard version of CPT, CPT_l, which allows for a gain-loss asymmetry only through the loss aversion parameter, the median (across participants) best-fitting value of the λ parameter was substantially larger than 1, λ = 1.40. 71.9% of the participants had a λ larger than 1. Moreover, CPT_l showed a considerably better fit than CPT_{nola}, which does not allow for an asymmetry between gains and losses (median BIC: 158.34 vs. 160.23). These results thus provide evidence for a gain-loss asymmetry in the data.

Is choice sensitivity higher in gambles involving losses? As previously stated, Yechiam and Hochman (2013a) argue that due to differences in attention, choice sensitivity should be higher when the gambles include a potential loss. We tested this prediction by modeling the data with CPT_{phila}, which allows for a gain-loss asymmetry in choice sensitivity only. As it turned out, there was no evidence for Yechiam and Hochman's hypothesis; in fact, we find the opposite pattern, with a higher choice-sensitivity parameter for gains than for losses, median values $\phi^+ = 0.18$ and $\phi^{\pm/-} = 0.09$, Wilcoxon test: W = 2,609, p = .0008 (two-tailed). This pattern of results was found for 58 of the 64 participants (91%).

Is probability sensitivity lower in mixed gambles? Consistent with Wu and Markle's (2008) hypothesis, the estimates for γ obtained with CPT_{gsm} indicated a lower probability sensitivity for mixed gambles than for single-domain gambles, median values $\gamma^{+\vee-} = 0.58$ and $\gamma^{\pm} = 0.86$, Wilcoxon test: W = 2,928, p = .0001 (two-tailed). Forty-eight out of 64 participants (75%) showed this pattern.

To summarize, these analyses indicate that people's choices reflect an asymmetry between gains and losses. Of two proposals concerning the specific nature of such asymmetries, we found support for only one, namely Wu and Markle's (2008) hypothesis that probability sensitivity is reduced in mixed as compared to single-domain gamble problems. Yechiam and Hochman's (2013a) proposal of a higher choice sensitivity for gambles involving losses was not supported (in fact, we found the opposite pattern). Next, we turn to the question of how well the different

[2] Note that while Glöckner and Pachur also compared some implementations of CPT, they neither tested Wu and Markle's (2008) sensitivity account, nor Yechiam and Hochman's (2013a) choice sensitivity account. More importantly, they also neither considered implementations of CPT in which only some of the parameters of the weighting function were estimated separately for gains and losses, nor implementations with a fixed λ parameter.

implementations of CPT summarized in Table 1 can account for people's choices. For instance, even if there is support for Wu and Markle's (2008) hypothesis of a lower probability sensitivity in mixed (as compared to single-domain) gambles, does an implementation of CPT allowing for this pattern (i.e., CPT_{gsm}) also perform well in terms of BIC?

Model Comparison

Figure 1 shows the median (across participants) BICs for each of the CPT implementations. As can be seen, the best-performing model is CPT_{dfixl}, which allows for gain-loss asymmetries in the elevation of the probability weighting function but sets $\lambda = 1$. Figure 2 shows the probability weighting function of CPT_{dfixl}, based on the median best-fitting parameter values. The figure shows that this model represents a gain-loss asymmetry by having a more elevated weighting function for losses than for gains, $\delta^- = 1.69$, $\delta^+ = 0.63$. Like models implementing the utility account, CPT_{dfixl} gives more weight to losses than to gains, but does this via the decision weights resulting from the weighting function rather than via the value function. CPT_{dfixl} not only achieved the best performance in terms of the median BIC, but also the overwhelming majority of individual participants (54.7%) were best accounted for by this model.[3]

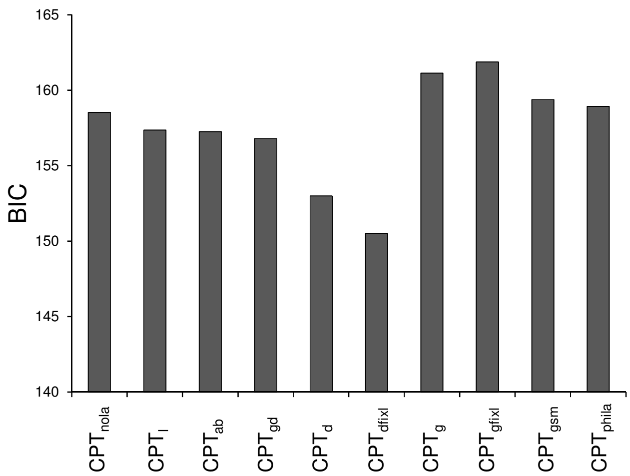

Figure 1: Performance of the different versions of CPT, as indicated by the median BIC (across participants)

Discussion

One of the fundamental assumptions in prospect theory is that negative prospects receive more weight in people's evaluations of risky alternatives than positive prospects. In general, our analyses provide support for this assumption by finding evidence for a gain-loss asymmetry. However, we pointed out that the parametric menagerie of CPT can, in principle, represent gain-loss asymmetries in many different ways, such as via outcome sensitivity, probability sensitivity, the elevation of the weighting function, and choice sensitivity. Crucially, our analyses showed that a model that assumes a gain-loss difference in the elevation of the weighting function and a symmetric value function provided the best account of people's choices. The common assumption of a kinked utility function thus does not seem to be necessary. Other proposed implementations of CPT, such as one that attributes gain-loss asymmetries to differences in the choice rule (Yechiam & Hochman, 2013a) or one that replaces the assumption of strict gain-loss separability by allowing for differences in probability sensitivity between single-domain and mixed gambles (Wu & Markle, 2008), were also clearly outperformed.

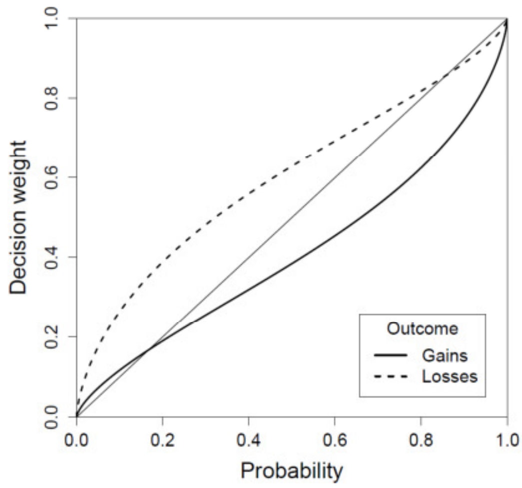

Figure 2: Shapes of the separate probability weighting functions for gains and losses of CPT_{dfixl}, the best performing model, when using the median best-fitting parameter estimates. The weighting functions differ only in terms of their elevation, which is higher for losses than for gains.

Our results seem to challenge the approach taken in previous tests of prospect theory that have focused on specific and individual gamble problems. For instance, using problems specifically designed to test gain-loss separability, Wu and Markle (2008) found evidence for a superiority of a version of CPT that allowed for different probability sensitivity in single-domain than in mixed gamble problems. By contrast, in the data set used here, where the gamble problems were not constructed to test specific assumptions of CPT (instead many of the gambles had been randomly generated; see Glöckner & Pachur, 2012, for details), Wu and Markle's modified version of CPT performed rather poorly (Figure 1). The results of our model comparison thus suggest that model developments based on focused tests may sometimes sacrifice a model's

[3] The second-best model in terms of selection frequency was CPT_{nola}, which best accounted for 17.2% of the individual participants. Interestingly, the second-best performing model in terms of the median BIC, CPT_d, best accounted for only 4.7% of the participants.

ability to account for choices more generally for its ability to account for idiosyncratic cases.

What does the superiority of the version of CPT with a more elevated probability weighting for losses than for gains (Figure 2) mean psychologically? The cognitive underpinnings of probability weighting are still rather little understood. This has led some researchers (e.g., Brooks & Zank, 2005; Zank, 2010) to focus more on what can be called "behavioral gain-loss asymmetries", that is, specific choice patterns that follow from gain-loss asymmetries on the value and/or probability weighting functions.

These open questions notwithstanding, our results suggest that if one's goal is to predict how people will decide between risky alternatives, modeling gain-loss asymmetries in terms of differences in probability weighting rather than utility weighting promises to be a more successful approach. Our conclusions thus resonate well with Prelec's (2000) assessment that "probability nonlinearity will eventually be recognized as a more important determinant of risk attitudes than money nonlinearity." (p. 89)

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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, 1384–1399.

Ahn, W.-Y., Busemeyer, J. R., Wagenmakers, E.-J., & Stout, J. C. (2008). Comparison of decision learning models using the generalization criterion method. *Cognitive Science*, *32*, 1376-1402.

Bernoulli, D. (1738/1954). Exposition of a new theory on the measurement of risk. *Econometrica, 22*, 23–36.

Birnbaum, M. H. (2008). New paradoxes of risky decision making. *Psychological Review*, *115*, 463-501.

Brooks, P., & Zank, H. (2005). Loss averse behavior. *Journal of Risk and Uncertainty, 31*, 301-325.

Fox, C. R., & Poldrack, R. A. (2008). Prospect theory and the brain. In Glimcher, P., Camerer, C., Fehr, E. & Poldrack, R. (Eds), *Handbook of neuroeconomics.* New York: Elsevier.

Glöckner, A., & Pachur, T. (2012). Cognitive models of risky choice: Parameter stability and predictive accuracy of prospect theory. *Cognition*, *123*, 21-32.

Goldstein, W. M., & Einhorn, H. J. (1987). Expression theory and the preference reversal phenomenon. *Psychological Review*, *94*, 236-254.

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

Harless, D. W., & Camerer, C. F. (1994). The predictive utility of generalized expected utility theories. *Econometrica*, *62*, 1251–1289.

Kass, R., & Rafferty, A. (1995). Bayes factors. *Journal of the American Statistical Association, 90*, 773-795.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica, 47,* 263–292.

Linhart, H., & Zucchini, W. (1986). *Model selection*. Oxford, England: John Wiley & Sons.

Locke, J. (1690/2004). *An essay concerning human understanding*. London: Penguin.

Luce, R. D. (1959). *Individual choice behavior: A theoretical analysis.* New York: Wiley.

Myung, I. J. (2000). The importance of complexity in model selection. *Journal of Mathematical Psychology, 44*, 190-204.

Pachur, T., & Scheibehenne, B. (2012). Constructing preference from experience: The endowment effect reflected in external information search. *Journal of Experimental Psychology: Learning, Memory and Cognition*, *38*, 1108-1116.

Peeters, G., & Czapinski, J. (1990). Positive-negative asymmetry in evaluations: The distinction between affective and informational negativity effects. In W. Stroebe, & M. Hewstone (Eds.), *European review of social psychology* (Vol. 1, pp. 33-60). Chichester, UK: Wiley.

Prelec, D. (2000). Compound invariant weighting functions in prospect theory. In D. Kahneman, & Tversky, A. (Eds.) *Choices, values, and frames* (pp. 67–92). Cambridge, UK: Cambridge University Press.

Schmidt, U., S. Traub. 2002. An experimental test of loss aversion. *Journal of Risk and Uncertainty*, *25*, 233-249.

Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics, 6,* 461-464.

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

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

Usher, M., & McClelland, J. L. (2004). Loss aversion and inhibition in dynamical models of multialternative choice. *Psychological Review*, *111*, 759–769.

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

Yechiam, E., & Hochman, G. (2013a). Losses as modulators of attention: Review and analysis of the unique effects of losses over gains. *Psychological Bulletin. 139,* 497-518.

Yechiam, E., & Hochman, G. (2013b). Loss-aversion or loss-attention: The impact of losses on cognitive performance. *Cognitive Psychology, 66*, 212-231.

Zank, H. (2010). On probabilities and loss aversion. *Theory and Decision*, *68*, 243-261.