# Composition Rules in Original and Cumulative Prospect Theory[†]

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**Abstract:** Original and cumulative prospect theory differ in the composition rule used to combine the probability weighting function and the value function. We test these composition rules by performing a novel test. We apply estimates of prospect theory's weighting and value function obtained from two-outcome cash equivalents, a domain where original and cumulative prospect theory coincide, to three-outcome cash equivalents, a domain where the composition rules of the two theories differ. We find systematic under-prediction for cumulative prospect theory and systematic over-prediction for original prospect theory. We use these findings to motivate new areas for theoretical and empirical investigation.

**Running Header**: Composition Rules in Prospect Theory

**Key Words**: Rank-dependent expected utility; prospect theory; composition rules

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# 1. INTRODUCTION

The St. Petersburg's Paradox challenged the notion that decision makers should choose the option that maximizes expected value. Bernoulli's (1738) resolution of the St. Petersburg's Paradox generalized expected value maximization in one important respect: the linear transformation of outcomes required by expected value was generalized to allow nonlinear transformations of outcomes, in particular, a logarithmic utility function. In the nearly three centuries since Bernoulli, expected value as a descriptive theory of decision making under risk has advanced in two additional respects. First, the linear treatment of probabilities under expected value and expected utility has been generalized under models that are "nonlinear in probability" (*e.g.*, Edwards, 1954; Kahneman & Tversky, 1979; Preston & Baratta, 1948). Second, the composition rule used in expected value, the sum of outcomes weighted by their respective probabilities, has been generalized (*e.g.*, Kahneman & Tversky, 1979; Quiggin, 1982).

A large family of modern descriptive theories of decision under risk depart from expected value maximization in three essential ways: the transformation of outcomes, the transformation of probabilities, and the composition rule that combines the two transformations. Prospect theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) has emerged as the frontrunner of these descriptive theories (see reviews of empirical evidence in Camerer, 1992, 1995; Starmer, 2000; Wu, Zhang, & Gonzalez, 2003). In prospect theory, outcomes are transformed by an S-shaped value function, concave for gains, convex for losses, and steeper for losses than gains; and probabilities are transformed by an inverse S-shaped probability weighting function, concave for small probabilities and convex for medium and large probabilities. A large body of empirical and theoretical investigation has supported these two aspects of prospect theory. In contrast, the third aspect of prospect theory, the composition rule, has received relatively little direct empirical attention. Moreover, the choice of the composition rule is not trivial: original prospect theory (OPT; Kahneman & Tversky, 1979) and its descendent, cumulative prospect theory (CPT; Tversky & Kahneman, 1992) differ in how these two transformation functions are combined, and, consequently in how gambles with three or more outcomes are valued.

This paper investigates the empirical merits and shortcomings of the two representations. We perform a novel test that exploits the following observation: CPT and OPT coincide for two-outcome gambles, but differ for gambles with three or more outcomes. This linkage allows us to perform a unique test—we estimate prospect theory parameters for two-outcome gambles, a domain where the two models concur, and apply these estimates to cash equivalents for three-outcome gambles, a domain where the models diverge. We then can test whether CPT and/or OPT fit three-outcome gamble data well, or whether there are systematic discrepancies.

The paper proceeds as follows. In Section 2, we present the two models, and review previous empirical research. In Section 3, we review one of our previous studies (Gonzalez & Wu, 1999) in which we estimate the probability weighting function on two-outcome gambles (where the two models coincide). We then use three-outcome gambles as a holdout sample to test how the two models perform. We find that both models are biased, but in a predictable manner: CPT underpredicts and OPT overpredicts the cash equivalents of three-outcome gambles. In Section 4, we conclude by suggesting how this analysis offers new insights about psychological processes underlying choice among complex gambles.

## 2. PROSPECT THEORIES

### 2.1. *Preliminaries*

In this section, we review original prospect theory (OPT, Kahneman & Tversky, 1979) and cumulative prospect theory (CPT; Tversky & Kahneman, 1992; see also Luce & Fishburn, 1991; Starmer & Sugden, 1988; Tversky & Wakker, 1993). Let $(p,x;q,y;1-p-q,z)$ denote a prospect that gives *p* chance at *x*, *q* chance at *y*, and $1-p-q$ chance at *z*, where $x>y>z\geq 0$. We first present Kahneman & Tversky's (1979) original formulation of OPT, when $z=0$:

$$\begin{gathered}(p,x;q,y;1-p-q,0)\succeq(p',x';q',y'1-p'-q',0)\\ \Leftrightarrow\\ V_O(p,x;q,y)=\pi(p)v(x)+\pi(q)v(y)\geq V_O(p',x';q',y')=\pi(p')v(x')+\pi(q')v(y')\end{gathered}\tag{1}$$

where $\pi:[0,1]\to[0,1]$ is a *probability weighting function* and $v(\cdot)$ is a *value function* defined with respect to a reference point, typically concave for gains and convex for losses, and $V_O(\cdot)$ is the OPT value functional. OPT requires that the *decision weights* attached to outcomes *x*, *y*, and 0 be $\pi(p)$, $\pi(q)$, and $1-\pi(p)-\pi(q)$, respectively.

Kahneman & Tversky (1979) only specified OPT for gambles with two non-zero outcomes. It is natural to extend (1) to the case in which $z>0$:

$$\begin{aligned}&(p,x;q,y;1-p-q,z)\succeq(p',x';q',y';1-p'-q',z')\Leftrightarrow\\ &V_O(p,x;q,y;1-p-q,z)=\pi(p)v(x)+\pi(q)v(y)+\pi(1-p-q)v(z)\geq\\ &\qquad V_O(p',x';q',y';1-p'-q',z')=\pi(p')v(x')+\pi(q')v(y')+\pi(1-p'-q')v(z').\end{aligned}\tag{2}$$

Of course, (2) can be further generalized to *n*-outcomes, as suggested by Camerer & Ho (1994) and Fennema & Wakker (1997):[1]

$$V_O(p_1,x_1;\ldots;p_i,x_i;\ldots;p_n,x_n)=\sum_{i=1}^{n}\pi(p_i)v(x_i).\tag{3}$$

OPT and its generalizations have several major problems. First, the representation is not well-defined for certain specifications of $\pi(\cdot)$. For example, if $\pi(p)>p$ for some *p*, then the

[1] See Luce (2000), however, for some criticisms of this generalization.

sum of the decision weights for $(p, x_1; ...; p, x_i; ...; p, x_n)$ will exceed one if $n > 1/p$. As a result, OPT can violate internality, *i.e.*, the cash equivalent of a gamble calculated using (3) can exceed the highest outcome of the gamble. For example, suppose that $v(x) = x$ and $\pi(.25) = .4$. Then the cash equivalence for the gamble $(.25;100;.25,90;.25,80;.25,0)$ is 108, which exceeds all outcomes of the gamble.

Second, the representation permits violations of stochastic dominance. To demonstrate, suppose that $\pi(.15) = .20$ and $\pi(.30) = .30$. Then, the representation implies that (.30,100) will have a lower value under (1) than the stochastically dominated $(.15,100;.15,100-\varepsilon)$ for sufficiently small $\varepsilon > 0$. As long as $\pi(\cdot)$ is nonlinear, stochastic domination violations are predicted (Fishburn, 1978). Kahneman & Tversky (1979) recognized this problem, and posited that transparent dominance would be detected (see, however, Birnbaum & Navarette, 1998; Kahneman & Tversky, 1986; Leland, 1998; see also, Starmer, 1999). However, many theorists found this solution unappealing because editing operations are imprecise and unparsimonious.

Finally, OPT allows certain patterns of intransitivity. Starmer (1999) showed that OPT might lead to the intransitive cycle of $(r, y; s, y-\varepsilon; 1-r-s, 0) \succ (p, x; 1-p, 0)$, $(p, x; 1-p, 0) \succ (q, y; 1-q, 0)$, and $(q, y; 1-q, 0) \succ (r, y; s, y-\varepsilon; 1-r-s, 0)$ if $\pi(r) + \pi(s) > \pi(q)$. Indeed, he looked for and found the predicted intransitivity empirically.

Quiggin (1982) avoided the problems of bilinear models like Kahneman & Tversky (1979) and others such as Edwards (1954) and Handa (1977) in his rank-dependent utility (RDU; see also, Green & Jullien, 1988; Quiggin, 1993; Quiggin & Wakker, 1994; Segal, 1989; Wakker, 1989; Yaari, 1987). Under this model, the value of $(p, x; q, y; 1-p-q, z)$, $V_C(p, x; q, y; 1-p-q, z)$, is given by:

$$V_C(p, x; q, y; 1-p-q, z) = \pi(p)v(x) + [\pi(p+q) - \pi(p)]v(y) + [1 - \pi(p+q)]v(z) . \qquad (4)$$

In contrast to OPT, the decision weight for an outcome depends not only on the probability of that outcome, but also on where that outcome is ranked relative to other outcomes in the gamble.

Note that stochastic dominance violations are prohibited under the RDU form of (4). To see why, note that $\lim_{y \to x} V_C(p, x; q, y) = V_C(p+q, x)$, which is not true for OPT. Returning to our previous example, under RDU, $V(.15,100;.15,100-\varepsilon) = \pi(.15)v(100) + [\pi(.30) - \pi(.15)]v(100-\varepsilon)$, which is strictly worse than $V(.30,100) = \pi(.30)v(100)$ for all $\varepsilon > 0$, provided that $\pi(\cdot)$ is non-decreasing. RDU generalizes easily and naturally to an arbitrary number of outcomes. Let $(p_1, x_1; ...; p_n, x_n)$ denote a gamble that gives $p_i$ chance at outcome $x_i$, where $x_i > x_{i+1}$. Then the generalization of (4) to an arbitrary number of outcomes is:

$$V_C(p_1, x_1; ...; p_n, x_n) = \pi(p_1)v(x_1) + \sum_{i=1}^{n}\left(\pi\left(\sum_{j=1}^{i} p_j\right) - \pi\left(\sum_{j=1}^{i-1} p_j\right)\right)v(x_i). \tag{5}$$

Tversky & Kahneman (1992) adopted RDU in their formulation of cumulative prospect theory. CPT basically consists of two separate RDU representations for losses and gains.

### 2.2. *Psychological Differences between OPT and CPT*

Fennema & Wakker (1997; also Diecidue & Wakker, 2001) noted that CPT was not merely a technical improvement over OPT that eliminated violations of stochastic dominance and generalized to an arbitrary number of outcomes, but that CPT and OPT had different empirical content. It is easy to see that OPT and CPT coincide for two-outcome prospects. The two models differ in terms of how prospects with three or more outcomes are valued. Specifically, OPT gives decision weight of $\pi(q)$ to the second highest outcome, whereas the decision weight given by CPT is $\pi(p+q) - \pi(p)$. Thus, CPT and OPT will lead to different valuations of gambles with three or more outcomes, except in the special case in which $\pi(\cdot)$ is linear.

Which of the two models best captures risky choice behavior? To answer this question, we first ask: when does CPT assign more weight to the middle outcome than OPT, and when is the opposite true? Formally, this questions boils down to whether $\pi(p+q)-\pi(p)$ is greater than or less than $\pi(q)$. Recent empirical studies on the probability weighting function provide a remarkably clear answer to that question: $\pi(p+q)-\pi(p)\leq\pi(q)$ for $p+q<1$, both at the level of aggregate data (Tversky & Fox, 1996; see also, Abdellaoui, 2000; Bleichrodt & Pinto, 2000; Fox & Tversky, 1998; Gonzalez & Wu, 1999) and at the level of the individual subject (Abdellaoui, 2000; Bleichrodt & Pinto, 2000; Gonzalez & Wu, 1999). The property, $\pi(p+q)-\pi(p)\leq\pi(q)$, has been called *lower subadditivity* (Tversky & Wakker, 1995) and can be thought of as capturing the boundary effect near zero often called the possibility effect.[2]

Although lower subadditivity indicates that OPT will overvalue a three-outcome gamble relative to CPT, this result itself does not establish which of the two models is more appropriate for modeling gambles with more than two outcomes. To begin answering this question, we need to understand the psychological differences in the composition rules employed by OPT and CPT. The models differ in an important psychological sense. OPT gives no precedence to the first or second outcome, *i.e.*, for a $(p,x;p,y)$ gamble, the highest outcome $x$ and second highest outcome $y$ have the same decision weight, $\pi(p)$. In contrast, under CPT and a lower subadditive

[2] Other properties of the weighting function have been inferred to explain the full pattern of risky choice behavior. At the other end of the probability scale, the weighting function has been found to be upper subadditive: $\pi(1)-\pi(1-p)\geq\pi(p+q)-\pi(p)$, which can be thought of as capturing the certainty effect. Other studies have shown that $\pi(\cdot)$ obeys stronger properties, namely concavity for small probabilities and convexity for medium and large probabilities (Abdellaoui, 2000; Gonzalez & Wu, 1999; Wu & Gonzalez, 1996, 1998). Concavity of small probabilities and convexity of large probabilities can be seen as generalizing the possibility and certainty effects captured in lower and upper subadditivity. Thus, the psychophysical property of diminishing sensitivity seems to

$\pi(\cdot)$, the second highest outcome is marginal or receives *less* weight than the highest outcome, $\pi(p+q)-\pi(p)$ versus $\pi(p)$. Thus, CPT generalizes the idea of diminishing sensitivity from merely being a distortion of probabilities (see Figure 1) to also affecting the weight attached to outcomes (Fennema & Wakker, 1997). In other words, probabilities held constant, extreme outcomes (highest and lowest) receive more weight relative to intermediate outcomes.

## 2.3. *Empirical Findings*

Almost all of the standard violations of expected utility are consistent with both OPT and CPT. The common-ratio effect (Kahneman & Tversky, 1979) involves only one non-zero outcome, and thus is explained identically by OPT and CPT (Prelec, 1998). The common-consequence effect (Kahneman & Tversky, 1979) involves at least three outcomes and therefore may lead to different predictions (Wu & Gonzalez, 1998). However, the common consequence form of the Allais Paradox and more generalized common consequence effect violations can be explained by OPT and CPT equally well (Wu & Gonzalez, 1996).[3] Goodness of fit tests paint a mixed picture. Wu & Gonzalez (1996) fit binary choice data collected to test common consequence effects using parametric specifications for $\pi(\cdot)$ and $v(\cdot)$. OPT fits the aggregate data slightly better, but is outperformed by CPT on 3 of 5 ladders. Camerer & Ho (1994) fit OPT and CPT to several datasets and found that OPT fits the data slightly better in maximum likelihood tests. Of course, estimation and goodness of fit statistics confound tests of models with assumptions about parametric forms of $\pi(\cdot)$ and $v(\cdot)$. More recently, Fennema & Wakker (1997) found that CPT explained Lopes (1993) data better than OPT. Wakker (2003) showed that the mixed gamble of data of Levy & Levy (2002) could be explained by CPT but not OPT.

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explain the inverse S-shaped probability weighting function as well as the S-shaped value function (Tversky & Kahneman, 1992).

[3] The two models use different properties of the weighting function to explain the patterns. For example, Wu & Gonzalez (1996) show that one condition for concavity under CPT is a condition for lower subadditivity under OPT.

# 3. STUDY

In this section, we present a study designed to test how OPT and CPT predict three-outcome gamble cash equivalents. OPT and CPT are identical for two-outcome gambles, see (1) and (4). We thus adopt the following strategy. We use cash equivalents for two-outcome gambles to fit parametric forms of the value and weighting function. We then use these estimates to predict cash equivalents for three-outcome gambles. The first step of this procedure is presented in great detail in Gonzalez & Wu (1999), so we only provide a brief summary here.

## 3.1. *Method*

We report data from 10 participants who were all graduate students in psychology. Each participant was paid \$50 for participating in 4 one-hour sessions, plus an additional fee (\$50 on average) received for playing out one of their choices using an incentive compatible elicitation procedure (Becker, DeGroot, & Marschak, 1964).

The design consisted of 165 two-outcome gambles: 15 outcome levels crossed with 11 levels of probability associated with the maximum outcome. Since all gambles offered nonnegative outcomes, prospect theory codes all outcomes as gains. Nine of these gambles (randomly chosen) were repeated to provide a measure of reliability. Except for the restriction that the identical gamble could not appear in two consecutive trials, the repeated gambles were randomly interspersed within the complete set of gambles. In addition to the two-outcome gambles, we included 22 gambles that had two nonzero outcomes and one zero outcome.

We used a computer program similar to that used in Tversky & Kahneman (1992). The program presented one gamble on the screen, and asked the participant to choose a cash equivalent (CE) from a menu of possibilities. The range of the choices spanned the range of the gamble (*i.e.*, in no case was a participant permitted a sure amount more extreme than the extreme amounts offered by the gamble). Once the cash equivalent was determined within a range (*e.g.*, between \$40 and \$60), a second screen with a new menu of choices was presented using a narrower range (*e.g.*, \$40 to \$60 in increments of \$4). By repeating this process, the program approached the cash equivalent to the nearest dollar (taking the midpoint of the final range). The procedure forced internality of the cash equivalent response; that is, all cash equivalents, CE, were forced to be between the highest outcome $X_H$ and the lowest outcome $X_L$ (symbolically, $X_L \preceq CE \preceq X_H$). We adopted the convention that on each screen the cash equivalent options appeared in descending order. Note that the elicitation procedure did not require participants to generate a cash equivalent (see, however, Fischer *et al.*, 1999). Rather, participants chose cash equivalents from a menu (for related procedures, see Bostic, Herrnstein & Luce, 1990; Tversky & Kahneman, 1992). The program presented gambles in random order to each participant.

## 3.2. *Two-outcome Gamble Results*

The subjects showed relatively high levels of reliability as measured by the maximum likelihood estimator of the intraclass correlation on the 9 repeated gambles (Haggard, 1958). The intraclass correlation on the median data was .99 (the median absolute deviation was \$1.50). The median of the 10 intraclass correlations computed on the individual subject data was .96, with a range of .60 to .99. Only two intraclass correlations were below .90 (the lowest .60 and the second lowest .87). Summary statistics such as median cash equivalents for each gamble are found in Gonzalez & Wu (1999), Table 1.

We performed parametric estimation of two-outcome cash equivalents using particular parametric specifications for $\pi(\cdot)$ and $v(\cdot)$. Researchers have used a variety of functional forms for the two functions $\pi(\cdot)$ and $v(\cdot)$ (Goldstein & Einhorn, 1988; Gonzalez & Wu, 1999; Lattimore *et al*. 1992; Prelec, 1998; Tversky & Kahneman, 1992). To determine whether a functional form was reasonable, Gonzalez & Wu (1999) first performed a non-parametric estimation using an "alternating least-squares" algorithm to estimate $\pi(.01), \pi(.05)$, $v(25),\ v(50),\ v(100),$ etc. We then used a nonparametric runs test to examine which functional forms for $\pi(\cdot)$ and $v(\cdot)$ were reasonable. The parametric functions $v(x) = x^{\alpha}$ and $\pi(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma} + (1-p)^{\gamma}}$ were not rejected for any of the 10 subjects or the median subject. In contrast, the one-parameter functions proposed by Tversky & Kahneman (1992) and Prelec (1998) were rejected for 6 of the 10 subjects. There were also three tests of subadditivity for each subject, and we observed only one violation (Subject 9).

We also performed a nonlinear regression using the parametric forms for $\pi(\cdot)$ and $v(\cdot)$ mentioned above to estimate the cash equivalents of the gambles. The parametric estimates for $\alpha$, $\delta$, and $\gamma$ appear in Table 2, and the weighting and value functions for the median data are plotted in Figure 2, while plots for the individual subjects are found in Gonzalez & Wu (1999). A striking regularity appears: all subjects as well as the median subject have a concave $v(\cdot)$ and inverse S-shaped $\pi(\cdot)$, with the exception of Subject #6 whose weighting function appears to be concave everywhere. However, there is also substantial heterogeneity in curvature and in elevation of $\pi(\cdot)$, and the two effects appear to be somewhat independent.

### 3.3. *Three-outcome Gamble Results*

We apply the parametric estimates of $\pi(\cdot)$ and $v(\cdot)$ to three-outcome gambles. Consider the gamble $(p, x; q, y; 1-p-q, 0)$. Using (3), the predicted cash equivalent (CE) under OPT, $CE_{\mathrm{OPT}}$, is given by:

$$CE_{\mathrm{OPT}} = v^{-1}\left(\pi(p)v(x) + \pi(q)v(y)\right),$$

where $v(x)=x^{\hat{\alpha}}$, $\pi(p)=\dfrac{\hat{\delta}p^{\hat{\gamma}}}{\hat{\delta}p^{\hat{\gamma}}+(1-p)^{\hat{\gamma}}}$, and $\hat{\alpha},\hat{\delta},\hat{\gamma}$ are the parameter estimates from the previous section. Similarly, CPT predicts the following cash equivalent:

$$CE_{\mathrm{CPT}}=v^{-1}\left(\pi(p)v(x)+[\pi(p+q)-\pi(p)]v(y)\right).$$

We then can compare the estimates under both models with the actual CE, $\mathrm{CE}_{\mathrm{act}}$.

We illustrate this procedure with the prospect, $(.40,400;.50,200,.10,0)$. The estimates for the median data (from Table 2) are $\hat{\alpha}=.49$, $\hat{\delta}=.77$, and $\hat{\gamma}=.44$, yielding $CE_{\mathrm{CPT}}=\$136$ and $CE_{\mathrm{OPT}}=\$190$ compared with the actual median CE is \$147. In this example, CPT underpredicts the CE, whereas OPT overpredicts the CE.

Figure 2 plots the predicted versus actual cash equivalents for both models using the median data. CPT is plotted in the bottom left panel and OPT is plotted in the bottom right panel. The pattern found in our illustration seems to generalize across the observations. We find that OPT overpredicts 17 of the 22 gambles, and CPT underpredicts 20 of the 22 gambles. Although both models fit well as measured by scatter of zero-intercept regression lines ($R^2=.99$ for CPT; $R^2=.97$ for OPT), estimates differ from actual cash equivalents in the same systematic way illustrated by the example: CPT underpredicts ($\beta=.81$, $p$<.0001) and OPT overpredicts ($\beta=1.13$, $p$<.01).

We perform the same analysis for each of the 10 subjects. There are problems with the four subjects (Subjects 2, 3, 5, and 6) who have supercertain weighting functions, $\pi(p)+\pi(1-p)>1$. For these subjects, there are some gambles for which OPT is poorly defined, *i.e.*, $1-\pi(p)-\pi(q)<0$. To illustrate, the prospect $(.50,200;.40,100;.10,0)$ is poorly defined for most supercertain subjects, *e.g.*, Subject 2's estimates of $\hat{\alpha} = .23$, $\hat{\delta} = 1.51$, and $\hat{\gamma} = .65$ give $\pi(.5) + \pi(.4) = 1.14$. We omit these gambles are the remaining analyses.

We observe the same pattern as above at the level of individuals. CPT underestimates cash equivalents for 7 out of 10 subjects and OPT overestimates cash equivalents for 8 out of 10 subjects. Zero-intercept regressions for each subject are given in Table 2. The regression analysis is performed only on the well-defined gambles.[4]

Finally, we compare the holdout sample predictions with the same analysis performed for expected utility. We estimated expected utility, $v(x) = x^{\alpha}$ and $\pi(p) = p$, on the 165 2-outcome gambles using nonlinear least squares. The parameter estimates $\hat{\alpha}$ for each subject and the median data are presented in Table 3. We then applied the estimated $\hat{\alpha}$ to predict the well-defined 3-outcome gambles. EU overestimates the cash equivalents for the median data and 8 of the 10 subjects.

Slopes for the zero-intercept regressions for each subject are given in Table 3, as well as goodness of fit ($R^2$) of these regressions for all three models (EU, OPT and CPT). The $R^2$ results suggest that globally the models do reasonably well at predicting three-outcome data from two-outcome data, but this measure masks the systematic over- and under-prediction.

## 4. DISCUSSION

Of the three components of choice models — value function, probability weighting function, and composition rules — composition rules have received the least empirical attention. The battle between OPT and CPT, the two most widely-studied "nonlinear in probability"

[4] Note also that ordinally the slope for CPT is less than the slope for OPT for all ten subjects, including the median data. This result follows directly if $\pi()$ is lower subadditive. Gonzalez & Wu (1999) found that 9 out of 10 subjects exhibited lower subadditivity. Subject 9 was the one subject who did not exhibit lower subadditivity.

models, to date has been mixed. In goodness of fit exercises, there has been a split decision: OPT and CPT each fare better for some data sets. OPT also explains some patterns that CPT cannot (*e.g.*, Wu, 1994), but CPT accommodates some patterns that OPT finds problematic (*e.g.*, Lopes, 1993).

In this paper, we take a different approach than previous researchers. We estimate parameter values on two-outcome gambles, where the models coincide, and then use these parametric estimates on a holdout sample of three-outcome gambles. We find that CPT systematically underestimates and OPT systematically overestimates three-outcome gamble cash equivalents.

We can rule out the critique that the prospect theory model overfits the two-outcome gambles. We performed a similar analysis using a holdout sample of the two-outcome gambles. To keep the sample sizes comparable with the three-outcome data, we randomly selected 22 two-outcome gambles as a holdout, then estimated parameters using the nonlinear least squares regression algorithm for the remaining 143 two-outcome gambles, and applied these parameters to predict cash equivalents for the 22 holdout gambles. Finally, we fit a zero-slope regression to see if there was a comparable systematic bias in over- or under-prediction (as we did with the 22 three-outcome gambles). This procedure was iterated 40 times to create different holdout samples. We found no indication of systematic over- or under-prediction of two-outcome gamble cash equivalents. The average slope over the 40 iterations for the median data was .999; the analyses for the individual subjects also had slopes extremely close to 1 with no systematic bias in either direction.

Although our analysis suggests that neither composition rule, CPT or OPT, works perfectly, goodness of fit measures indicate that both models do pretty well in explaining three-outcome cash equivalent data. Moreover, CPT does significantly better at explaining three-outcome data than expected utility. Thus, we do not regard our analysis alone as good reason to discard either prospect theory as a model. Our view is that the glove fits, but some alterations are needed if the wearer wants a snugger fit. On a pragmatic level, CPT is both parsimonious (aggregate data are explained well using only one more parameter than expected utility, Gonzalez & Wu, 1999), and tractable because using CPT is just like using EU with transformed probabilities. For those interested in alterations, we suggest some promising research strategies, both empirical and theoretical in nature.

We begin by considering modeling strategies. To help us understand what a more descriptively accurate model might require, we return to our earlier discussion of CPT. Recall that CPT generalizes the idea of diminishing sensitivity from probabilities to outcomes in a manner that preserves stochastic dominance. However, eliminating stochastic dominance violations comes at a cost. To demonstrate, consider a gamble, $(p, x; 1-p, 0)$. Imagine that the gamble is improved by shifting $q$ chance at 0 to $y$. If $y < x$, the resulting gamble is $(p, x; q, y; 1-p-q, 0)$, whereas if $y = x$, the resulting gamble is $(p+q, x; 1-p-q, 0)$. The decision weight attached to the outcome $y$ is the same in both cases: $\pi(p+q) - \pi(p)$. Psychologically, however, we might expect that the decision weight attached to $y$ when $y < x$ might be higher than the decision weight attached to $y$ when $y = x$. In the former case, $y$ is distinctive and draws attention, whereas in the second case, $y$ is assimilated with $x$. There are analogous findings in other areas of judgment and decision making. Support theory (Tversky & Koehler, 1994) organizes the empirical observation that the probability assigned to an event increases as the event is broken into constituent pieces. Research on attribute splitting in multi-attribute decision making has shown that the weight on an attribute increases when that attribute is split into sub-attributes (Weber *et al.*, 1989). Finally, studies of event-splitting suggest that coalescing is violated (*e.g.*, Birnbaum & Martin, 2003; Luce, 2000; Starmer & Sugden, 1993).

While CPT has the attractive feature of generalizing diminishing sensitivity from probabilities to outcomes, OPT has the feature that outcomes that are distinctive from others get more weight because of the subadditivity of $\pi(\cdot)$. One compromise is to join together some attractive features of both to form a hybrid model:

$$V_H(p,x;q,y;1-p-q,z) = \pi_1(p)v(x) + \pi_2(q)v(y) + \pi_3(1-p-q)v(z) ,$$

where $\pi_1(p) \geq \pi_2(p)$ and $\pi_3(p) \geq \pi_2(p)$ for all $p$. Diminishing sensitivity of outcomes is captured by the requirement that the probability weighting function for the highest outcome be at least as elevated as that for the second highest outcome. On the other hand, returning to the example in the previous paragraph, the decision weight attached to $y$ when $y < x$ might be higher than the decision weight attached to $y$ when $y = x$, *i.e.*, $\pi_2(q) > \pi_1(p+q) - \pi_1(p)$. Of course, the hybrid model has the distinct disadvantage of being more complicated and parameter-heavy, but elevation differences between $\pi_1(p)$ and $\pi_2(p)$ can be parsimoniously accommodated in two-parameter probability weighting function forms like that used in Gonzalez & Wu (1999). This hybrid model is identical to Birnbaum's RAM model (*e.g.*, Birnbaum & Navarette, 1998).

Beyond modeling, more empirical research is clearly needed. Such research might take a couple of different forms. The first form involves direct test of the axioms underlying CPT and OPT. The analyses performed in this paper, while revealing, are indirect. Test of axioms are considerably more precise. The literature is full of axiom systems for CPT and RDU (*e.g.*, Abdellaoui, 2002; Wakker & Tversky, 1993), but complete axiom systems for OPT are lacking. It is possible however to generate necessary axioms for OPT. Some axioms, such as the distributivity axiom, $(p,x_1;p,x_2;1-2p,0) \sim (p,x_0;1-2p,0)$ implies that $(q,x_1;q,x_2;1-2q,0) \sim$

$(q, x_0; 1-2q, 0)$, have appeared already in the literature and are easily testable (Kahneman & Tversky, 1979). Other axioms, such as tradeoff consistency axioms analogous to those offered for CPT, can help isolate regions in which CPT and OPT differ qualitatively as well as quantitatively. Current investigations of this sort are underway (Zhang, Wu, & Abdellaoui, 2003).

A second form of empirical research might consider what kind of psychological processes are not modeled or inadequately modeled by the existing theories. One avenue is to consider attention more directly. Decision weights can be thought of as capturing the amount of attention devoted to each outcome. Such an interpretation of decision weights is not new. Many researchers including Lopes & Oden (1999), Wakker (1991), and Weber (1994) have offered motivational accounts of decision weights as capturing the balance between security and potential, optimism and pessimism, and asymmetric loss functions. We suggest in addition that there may be a cognitive explanation involving attention. How a gamble is presented to the respondent may influence how much attention each outcome garners. For example, attention to middle outcomes might differ if a distributional presentation such as that used by Lopes & Oden (1999) is used rather than a verbal presentation such as that used in Tversky & Kahneman (1992). Mouselab offers one promising way of studying attention by measuring how long and often subjects attend to particular outcomes and probabilities (Costa-Gomes *et al.*, 2001; Johnson *et al.*, 2002; Payne *et al.*, 1993).

An additional avenue is the understudied area of editing rules. Kahneman & Tversky (1979) proposed two phases of a choice process, an edited phase and an evaluation phase: “The function of the editing phase is to organize and simplify subsequent evaluation and choice.” (p. 274). Although editing is undoubtedly important, there have been very few direct studies of editing, probably because editing rules are almost surely highly imprecise, unparsimonious, and situationally dependent (for an exception, see Wu, 1994).

We suggest that the psychophysics of the weighting and value function for simple two-outcome prospects might be basic. Beyond that, the process is to some extent constructive: subjects will use editing operations to simplify the gamble and hence the choice process. Subjects then apply the two-outcome weighting and value function to the simplified prospect as best they can (for examples, see Wu, 1994).

A deeper analysis of editing operations may shed new light on decision processes. Consider two potentially contradictory observations. First, parametric estimations of the weighting function have been very similar whether the underlying task is choice (Camerer & Ho, 1994; Wu & Gonzalez, 1996) or matching (Tversky & Kahneman, 1992; Gonzalez & Wu, 1996; Abdellaoui, 2000; Bleichrodt & Pinto, 2000). Second, some gambles give rise to pricing-choice preference reversals or cannot be easily explained by either prospect theory (Alarie & Dionne, 2001; Lichtenstein & Slovic, 1971).

This seeming contradiction can be partially resolved by recognizing that editing operations might take two forms: within-gamble operations such as combination or across-gamble operations such as cancellation. In pricing tasks, for example, only within-gamble operations are available, but in choice tasks, a combination of across- and within-gamble operations may be used. [Note that the task in our study was pricing, thus only within-gamble operations are relevant to the present data.] Of course, estimation masks the imperfect fit of the model for particular gambles as well as particular choice pairs. It may very well be that the composition rules studied here are never literally applied, yet may nevertheless adequately approximate the behavior of subjects who use a myriad of editing operations to simplify gambles.

We close by suggesting how the psychology of editing could be approximated by one of the two composition rules. Whether the composition rule used is more CPT-like or more OPT-like may depend on how reasonable it is to evoke editing rules such as combination. Consider the gamble $(.3, x; .1, 100; .6, 0)$. Whether the decision weight attached to the middle outcome, 100, is more CPT-like, $\pi(.4) - \pi(.3)$, or more OPT-like, $\pi(.1)$, may very well depend on *x*. If $x = 110$, then the highest and second highest outcome are more naturally combined or cumulated, thus resulting in a CPT-like composition rule. If, on the other hand, $x = 200$, combination of this sort is less likely, and 100 may be isolated, thus resulting in an OPT-like rule. More generally, in choice tasks whether 200 and 100 are viewed as similar may depend on the components of the alternative gamble. For example, 200 and 100 look dissimilar when the alternative is $(.5, 150; .5, 0)$, but may be viewed as quite similar when the alternative is $(.005, 15000; .995, 0)$. We look forward to future investigations of this sort.

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**Figure 1**

A typical probability weighting function, $\pi(\cdot)$. The weighting function is inverse S-shaped, concave for small probabilities and convex for medium to large probabilities, and intersects the identity line below ½.

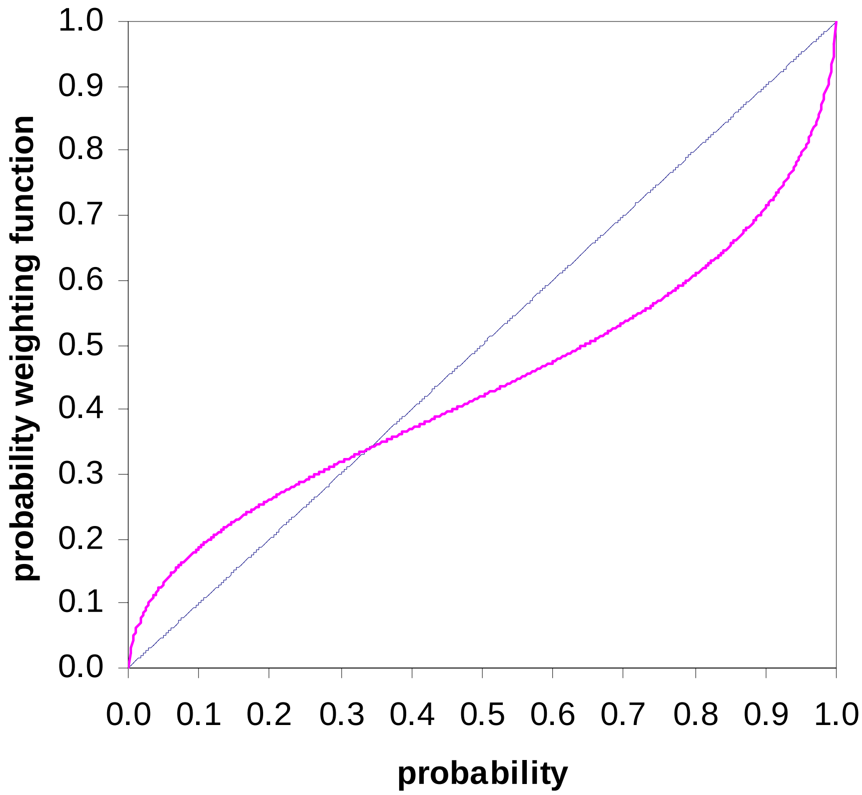

**Figure 2**

The panels show the weighting and value function for the median data, as well as the predicted cash equivalents under OPT and under CPT.

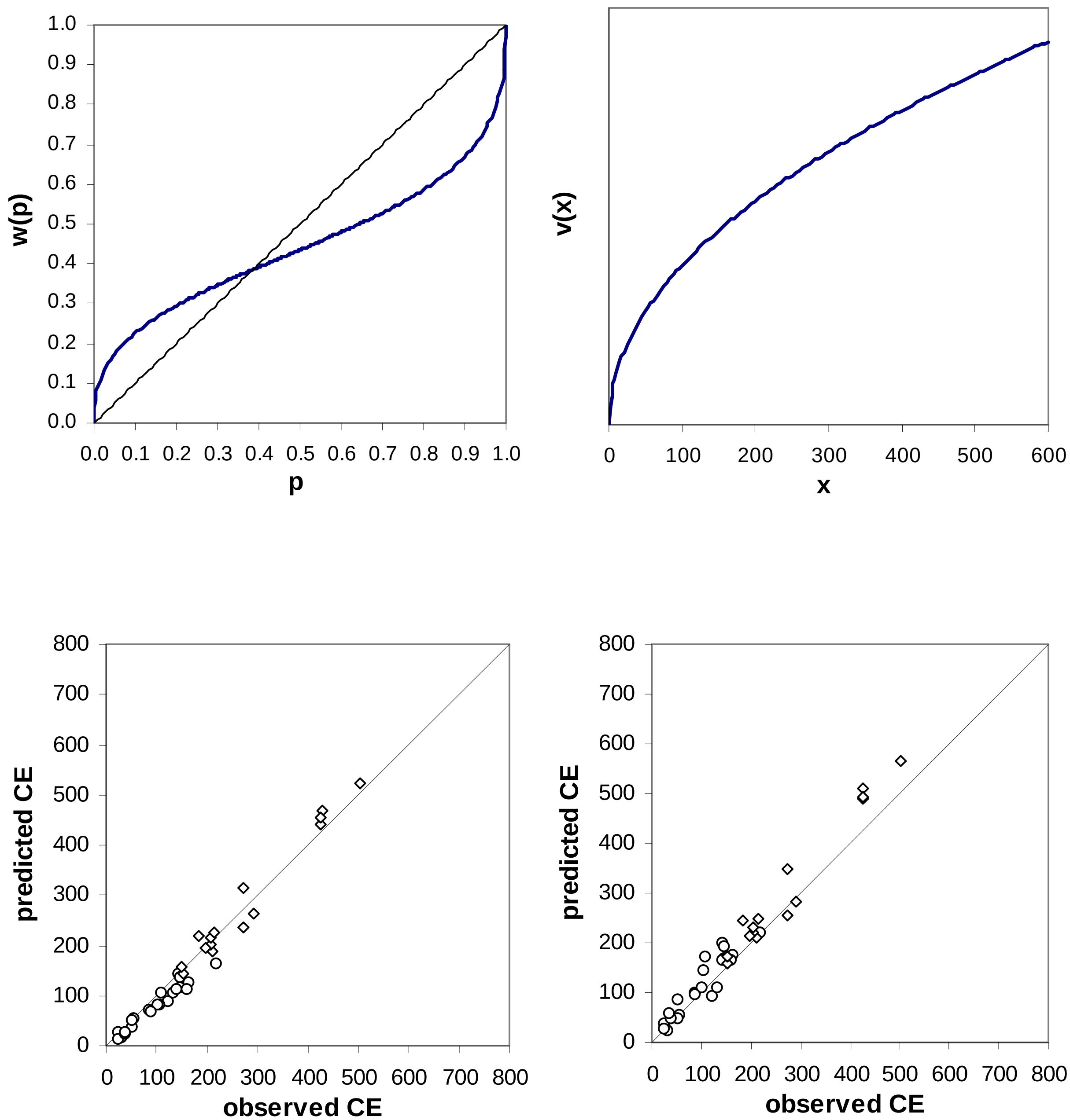

**Table 1**
Three-outcome gambles, $(p, x; q, y, 1-p-q, z)$, used in study. Cash equivalents for each gamble are also given, as well as cash equivalents under CPT and OPT, predicted from parameters fitted on two-outcome gambles.

| Gambles | | | | | | Summary Statistics | | |
|---|---|---|---|---|---|---|---|---|
| *p* | *x* | *q* | *y* | 1-*p*-*q* | *z* | Median Cash Equivalent | CPT prediction | OPT prediction |
| 0.80 | 400 | 0.10 | 200 | 0.10 | 0 | 216.5 | 163.7 | 220.9 |
| 0.80 | 300 | 0.10 | 200 | 0.10 | 0 | 162 | 126.3 | 176.9 |
| 0.40 | 300 | 0.50 | 200 | 0.10 | 0 | 159 | 112.9 | 166.1 |
| 0.50 | 300 | 0.40 | 200 | 0.10 | 0 | 147 | 115.8 | 169.6 |
| 0.40 | 400 | 0.50 | 200 | 0.10 | 0 | 147 | 136.0 | 194.0 |
| 0.50 | 400 | 0.40 | 200 | 0.10 | 0 | 143 | 141.9 | 201.1 |
| 0.40 | 300 | 0.50 | 200 | 0.10 | 0 | 141 | 112.9 | 166.1 |
| 0.50 | 200 | 0.49 | 100 | 0.01 | 0 | 132 | 106.1 | 108.7 |
| 0.50 | 150 | 0.49 | 100 | 0.01 | 0 | 121 | 89.8 | 92.3 |
| 0.50 | 400 | 0.25 | 200 | 0.25 | 0 | 108.5 | 105.6 | 173.6 |
| 0.50 | 300 | 0.25 | 200 | 0.25 | 0 | 105 | 83.3 | 144.4 |
| 0.80 | 200 | 0.10 | 100 | 0.10 | 0 | 102 | 81.8 | 110.4 |
| 0.40 | 200 | 0.50 | 100 | 0.10 | 0 | 88 | 68.0 | 97.0 |
| 0.50 | 200 | 0.40 | 100 | 0.10 | 0 | 86 | 71.0 | 100.6 |
| 0.50 | 100 | 0.49 | 50 | 0.01 | 0 | 56 | 53.0 | 54.3 |
| 0.50 | 200 | 0.01 | 100 | 0.49 | 0 | 52 | 37.1 | 48.8 |
| 0.50 | 200 | 0.25 | 100 | 0.25 | 0 | 52 | 52.8 | 86.8 |
| 0.10 | 300 | 0.10 | 200 | 0.80 | 0 | 39 | 22.8 | 49.2 |
| 0.10 | 400 | 0.10 | 200 | 0.80 | 0 | 36 | 28.8 | 57.9 |
| 0.50 | 100 | 0.01 | 50 | 0.49 | 0 | 30 | 18.6 | 24.4 |
| 0.50 | 150 | 0.01 | 100 | 0.49 | 0 | 25 | 27.9 | 38.1 |
| 0.10 | 200 | 0.10 | 100 | 0.80 | 0 | 23.5 | 14.4 | 28.9 |

**Table 2**

Parameter estimates from the standard nonlinear least squares regression with a power value function (exponent = $\alpha$) and the linear in log odds weighting function ($\delta$ and $\gamma$). Values in parentheses are standard errors.

| | Parameter Estimates | | |
|---|---|---|---|
| Subject | $\alpha$ | $\delta$ | $\gamma$ |
| 1 | 0.68 (.10) | 0.46 (.11) | 0.39 (.03) |
| 2 | 0.23 (.06) | 1.51 (.46) | 0.65 (.04) |
| 3 | 0.65 (.12) | 1.45 (.35) | 0.39 (.02) |
| 4 | 0.59 (.05) | 0.21 (.04) | 0.15 (.02) |
| 5 | 0.40 (.08) | 1.19 (.32) | 0.27 (.02) |
| 6 | 0.68 (.06) | 1.33 (.15) | 0.89 (.03) |
| 7 | 0.60 (.06) | 0.38 (.07) | 0.20 (.02) |
| 8 | 0.39 (.07) | 0.38 (.11) | 0.37 (.04) |
| 9 | 0.52 (.08) | 0.90 (.18) | 0.86 (.04) |
| 10 | 0.45 (.09) | 0.93 (.26) | 0.50 (.03) |
| Median | 0.49 (.04) | 0.77 (.10) | 0.44 (.01) |

**Table 3**

Slope of Regression Line for Zero-Intercept Regressions (Predicted CE vs. Observed CE) for Cumulative Prospect Theory (CPT) and Original Prospect Theory (OPT). We omit gambles that are poorly defined by OPT for supercertain subjects (number of relevant observations denoted by *n*).

*** Significantly below 1 (.05, .01, .001 level), $^{+++}$ Significantly above 1 (.05, .01, .001 level)

| | | Model | |
|---|---|---|---|
| Subject | *n* | CPT | OPT |
| 1 | 22 | $0.60^{***}$ | $0.71^{***}$ |
| 2 | 6 | $0.25^{***}$ | $0.47^{***}$ |
| 3 | 6 | $0.77^{**}$ | $1.30^{++}$ |
| 4 | 22 | $0.47^{***}$ | $0.78^{*}$ |
| 5 | 6 | 1.12 | $3.04^{+++}$ |
| 6 | 12 | $0.92^{***}$ | 1.03 |
| 7 | 22 | $0.58^{***}$ | 0.93 |
| 8 | 22 | $0.31^{***}$ | $0.37^{***}$ |
| 9 | 22 | $1.19^{+++}$ | $1.20^{+++}$ |
| 10 | 22 | $0.76^{***}$ | 1.11 |
| Median Subject | 22 | $0.81^{***}$ | $1.13^{++}$ |

**Table 4**

Slope of Regression Line for Zero-Intercept Regressions (Predicted CE vs. Observed CE) for Expected Utility (EU). We omit gambles that are poorly defined by OPT for supercertain subjects (see Table 2). Raw score $R^2$ are presented for the three models.

$^{***}$ Significantly below 1 (.05, .01, .001 level), $^{+++}$ Significantly above 1 (.05, .01, .001 level)

| Subject | $EU\ \hat{\alpha}$ | EU Slope | EU $R^2$ | OPT $R^2$ | CPT $R^2$ |
|---|---|---|---|---|---|
| 1 | .89 (.006) | $1.35^{+++}$ | .92 | .92 | .92 |
| 2 | .93 (.016) | 1.41 | .88 | .87 | .65 |
| 3 | .97 (.003) | $0.53^{**}$ | .65 | .95 | .91 |
| 4 | .73 (.013) | $4.16^{+++}$ | .70 | .71 | .76 |
| 5 | .90 (.005) | $1.79^{++}$ | .91 | .81 | .91 |
| 6 | .99 (.001) | 0.97** | .99 | .99 | .99 |
| 7 | .82 (.007) | $2.31^{+++}$ | .85 | .87 | .88 |
| 8 | .79 (.011) | $1.74^{++}$ | .63 | .64 | .70 |
| 9 | .96 (.003) | $1.49^{+++}$ | .94 | .96 | .96 |
| 10 | .93 (.004) | $1.29^{++}$ | .91 | .92 | .91 |
| Median Subject | .91 (.004) | $1.57^{+++}$ | .97 | .97 | .99 |